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Trade Shocks and Firms Hiring Decisions: Evidence from Vacancy Postings of Chinese Firms in the Trade War*

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Abstract

This paper studies the hiring behavior of firms exposed to the recent China-US trade war. Our analysis leverages information from a Chinese online job board and a firm-level measure of tariff exposure obtained from customs transactions data. Firms that are more exposed to US tariffs on Chinese goods responded by posting fewer job vacancies and offering lower wages. The latter is partly balanced out by increased non-wage compensation. We also find a negative relationship between US-tariff exposure and the educational background required in firms' job ads. China's retaliatory tariffs against the US does not appear to have a statistically significant systematic impact on hiring. The paper also reports heterogeneous adjustment patterns across firms of different size, ownership and product mix. Overall, the trade war reveals to have negative impact on firms and job-seekers in China.

Keywords: Trade war, tariffs, online job vacancies, firm recruitment
JEL Code: D22, F13, F14, J23

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All errors are ours.

1 Introduction

The recent escalation of the US-China trade war resulted in a substantial disruption of trade between the two countries. US imports from China hit a 5-year low in 2019, ranging about 33bn US dollars below their value from 2015. US exports to China were about 9.5bn dollars below 2015-levels. Comparing shipments in 2016-2017 to the years 2018-2019, US imports from China decreased by 14-23 percent, while US shipments to China decreased by 15-27 percent.[1]

Disruptions are not limited to aggregate trade flows. While exposed exporting firms have to cope with an artificial increase in the price of their sold products, importers have to pay more for their purchases or find new suppliers. Both see their competitiveness eroding and lower sales and profits force them to re-optimize their cost structure and investment decisions, including their labor demand.

In this paper, we use newly collected information from online job-vacancy postings in China to document firm-level reactions to the trade war reflected in labor demand. By observing information on the number and content of online job ads between May and November 2019, we capture the most recent round of US tariff increases and Chinese retaliation. This enables us to evaluate responses to the trade war at an early stage of firms' hiring process along several dimensions. Our results provide novel insights into the propagation of short-term responses by firms to adverse trade policy shocks.

An important feature of the trade war is that the introduction of new tariffs did not follow a rule-based rationale in the context of conventional WTO anti-dumping or safeguarding regulations. In fact, the US administration first based tariffs on national security interests, but later raised tariffs on goods even if they were not currently imported from China (Bown and Kolb, 2019; Handley et al., 2020a). This constitutes a credible setup for a key identifying assumption: that Chinese firms had no influence on the timing, magnitude and coverage of the tariffs. Moreover, the magnitude and product coverage of the additional (discriminatory) tariffs has been unseen for decades, which enables us to study a policy experiment that is unique in contemporary economic history.

Indeed, the theoretical linkages between tariffs and firms' hiring behavior can be manifold and predicted outcomes are potentially ambiguous. Some intuition can be derived from trade models with heterogeneous firms and imperfect product-market competition (Melitz, 2003; Melitz and Ottaviano, 2008; Melitz and Trefler, 2012). Depending on mod-

[1] Calculations use monthly trade statistics reported by the US International Trade Commission (USITC), where trade values are reported in current prices and exclude any costs of surcharges or tariffs. Calculated percentage reductions depend on the assumed underlying trend in aggregate bilateral trade. Figure B.1 visualizes these numbers.

eling assumptions and initial product-market conditions, tariffs are either fully or partly passed through to customers, while lower profits follow in both cases. With (partial) pass-through and downward-sloping demand, exporters face lower sales, downscale their production, and might eventually demand less labor. Moreover, (partial) absorption of a tariff-induced price increase might result in lower salary offers by firms, as they seek to preserve market access (and restore profit margins) through lowering their factor costs.[2]

Adjustments by firms facing new tariffs on their imports after Chinese retaliation are more difficult to predict. On the one hand, firms sourcing intermediate inputs from the US might switch to alternative (second best) suppliers, which potentially undermines their competitiveness *vis-à-vis* less exposed firms (e.g., Handley et al., 2020b). Fewer job postings could reflect an ensuing decline in labor demand. On the other hand, instead of switching suppliers, exposed firms could manufacture the tariffed inputs themselves and hire additional workers.[3] This is reminiscent of the rationale proclaimed by the US administration when it imposed additional tariffs on Chinese goods: higher tariffs might boost domestic production and employment through import substitution.

At least two elements complicate such reasoning. First, the US-China trade war has created substantial economic uncertainty among Chinese firms (Benguria et al., 2020). While selection, timing, and magnitude of additional tariffs did not follow any rule-based mechanism, also their duration is unknown. Second, job vacancy postings signal firms' willingness to invest *now* into their *future* workforce. With the future being uncertain, such investments might be delayed, so that a positive employment effect becomes less likely to materialize in the short run (Bloom et al., 2007; Stein and Stone, 2013; Ghosal and Ye, 2015). Further complicating elements relate to the characteristics of the Chinese labor market itself. Depending on the intensity at which firms compete for qualified staff, there might be more or less room for adjustments in published salary offers. Similarly, formal and informal labor market institutions that determine the costs of hiring, firing and delayed hiring might influence firms' adjustments.

Against this background, we present reduced-form evidence on the effects of tariffs on firms' labor demand, as reflected by their publicly posted hiring announcements via

[2] A recent article in *The Wall Street Journal* (WSJ, 2020) reports that Chinese toy manufacturers respond to additional US tariffs by using cheaper (and lower quality) inputs. Similar cost-saving adjustments could occur via offered wages. More systematic evidence from Cavallo et al. (2019) suggests that additional US tariffs faced by (Chinese) exporters are almost entirely passed through, while importing retailers partly absorb them at the expense of lower margins. In turn, US exporters facing retaliatory tariffs tend to lower their prices.

[3] Hummels et al. (2018) identify such "make-or-buy decisions" as one key element of offshoring (or re-shoring in the present case), which depends on the relative costs of sourcing. An *ad-hoc* switch to in-house production might also be realistic for firms that already produce certain varieties of their imported goods (Bernard et al., 2020).

a major Chinese job-portal. A main advantage of using online job advertisements is their rich information that is typically not observable in firm-level census or survey data. This includes, for instance, the number of open positions and their change over time, as well as the average wage offered for a particular job. Besides this, we are able to observe different forms of non-wage compensation (such as bonuses, subsidies and insurance packages) as well as specifications of job prerequisites (e.g., previous working experience or educational background). Our identification strategy relies on a firm-specific measure of exposure to the trade war, which we construct based on pre-trade war information about firms' product mix and trade partners in a matched firm-level customs data set.

Our panel regression results suggest that firms exposed to higher US tariffs responded by posting systematically fewer job ads. The reduction amounts to about 2.4-3.2 percent for an average firm, which adds up to about 5,600 fewer job postings in total. A negative impact is also found for the average wage compensation indicated in the job ads. Our estimated 0.5 percent decrease corresponds to about $70 lower earnings per year in an average job offer. Such reductions appear to be balanced out partly by other forms of compensation, such as bonuses. This might suggest that firms shift towards more flexible and performance-based compensation schemes as they face higher US tariffs. Moreover, we find a robust and negative relationship between US-tariff exposure and the required educational background, while requirements on previous job experience do not show any statistically significant response. The reduction in educational-background requirements might reflect that US tariffs disproportionately targeted relatively skill-intensive products.[4]

In contrast to these findings, we do not detect any comparable systematic adjustments to China's retaliatory tariffs on US products. While the sign of the corresponding coefficient tends to be the opposite of that for US tariffs, their magnitude and precision are substantially lower. This is similar to findings of related studies in the US, where import tariffs fail to create new jobs or boost manufacturing sector performance (e.g. Goswami, 2020; Flaaen and Pierce, 2020). In fact, any notable producer gains seem to be either offset by costlier imported inputs, or by the recent (and potentially temporary) nature of these tariffs that prevents firms from investing into new jobs quickly.[5] Our main findings are maintained after submitting our results to a number of robustness checks, although we

[4]This interpretation is in line with Atkin (2016); Blanchard and Olney (2017) and also with the notion that US tariffs disproportionately targeted intermediate inputs (Handley et al., 2020a). A reduction in educational background requirements could also be the result of changing organizational hierarchies in exposed firms (Caliendo et al., 2020): establishments facing a negative demand shock reduce the relative size of their management layer.

[5]This is in line with theories on firms' investment behavior under policy uncertainty, considering a significant option value of waiting (e.g. Handley, 2014; Handley and Limão, 2015).

document some differential responses across firms of different size, ownership, or product mix.

Overall, the US-China trade war appears to hurt both firms and job-seekers, creating losers on both sides. This conclusion is in line and complementary to existing studies on the trade war, which focus primarily on the US economy (Fajgelbaum et al., 2020; Amiti et al., 2019, 2020; Flaaen and Pierce, 2020; Handley et al., 2020a; Waugh, 2019; Goswami, 2020) or on trade and investment effects in third countries (Meinen et al., 2019; Egger and Zhu, 2019). We add to this literature by shedding light on the experience of Chinese importers and exporters during this episode of political escalation.

Our reduced-form evidence provides novel insights on short-term labor-market effects of the trade war. In contrast to the related studies for the US, we do not rely on regional administrative data, but uncover another layer by observing adjustments in the number and content of vacancy postings over time. Our findings are also similar to Javorcik et al. (2019), who report decreasing online-hiring activity in the UK after the Brexit referendum, due to increased trade policy uncertainty. While their approach relies on differential industry-sector and regional exposure to a major trade-policy shock, we explicitly control for aggregate variation along these dimensions to document similar and more nuanced adjustments *within* firms. Our findings corroborate evidence on the adverse effects of international political disintegration and uncertainty on economic activity.

By using newly collected data from a Chinese job board, our study also contributes to a growing literature which uses online vacancy postings to analyze and compare labor market dynamics in different countries. We introduce and describe this data in detail in Section 2, along with the sample used to carry out the analysis of the present paper. In Section 3, we provide additional background information on key events of the trade war, which are relevant for our identification. Section 4 explains our empirical strategy to identify the impact of tariffs on labor demand. Section 5 presents our results, including robustness checks and an exploration of heterogeneous responses across firms. Section 6 concludes.

2 Online job-vacancy data

We join a growing literature that uses job vacancy data to understand a variety of issues related to the labor market. Since the early study of Kuhn and Skuterud (2004), several papers exploit such information to study, among others, the relationship between firm performance and skill demand (Deming and Kahn, 2018; Kahn and Hershbein, 2018), firm's financial health and its recruiting outcomes (Brown and Matsa, 2016), as well as other demand-side features, such as gender discrimination (Kuhn and Shen, 2013), search effort and search duration (Faberman and Kudlyak, 2016), or labor market concentration for specific types of jobs (Azar et al., 2018). While most job-vacancy datasets stem from English job-ad platforms,[6] Kuhn and Shen (2013) are an exception by using vacancy data from the Chinese recruitment website *Zhaopin.com*. Our data is similar to theirs, but has broader coverage and overall greater resemblance with China's cross-regional and sectoral employment patterns reported in administrative data, as we outline below.

2.1 Data source and collection

Our data comes from *Qian Cheng Wu You 51job.com* (hereafter, 51job.com), a leading company for recruiting and human resource services in China. According to its recent annual reports, the platform mainly targets (early career) white-collar workers in a wide range of job categories. Since the launch of the platform in 1999, the company counts about 150 million registered job-seekers and estimates that, today, almost 500,000 unique employers use their online recruiting services every year.[7]

We are interested in the publicly available information provided to job-seekers via online vacancy postings at 51job.com, which comes in a standardized format as shown in Figure A.1(a). Information states offered salary and non-wage compensation, job requirements regarding educational background, working experience, language and computer skills, a detailed job description with keywords, and the working location. Because job ads are linked to a firm's page, we also have basic information on the firm characteristics, such as ownership, scale of employment, and main industry. This information allows us investigate labor demand along several dimensions while controlling for factors reflecting unobserved characteristics of a location, industry, or firm. Via a unique URL-based vacancy-identifier (see panel (b) of Figure A.1), we can track hiring activity of over time.

We collected information systematically since May 2019 to construct a dataset with monthly frequency covering the period through November 2019. To obtain an as complete as possible record of job-postings, we collected information several times per month and deleted duplicates thereafter to avoid double-counting (see Section A.2 in our Data Appendix). This procedure resulted in 1.7-2.7 million distinct job vacancies per month,

[6] Examples are Craiglist (Kuhn and Skuterud, 2004), the Job Openings and Labor Market Turnover (JOLTS) survey from the BLS (Davis et al., 2012, 2013), Burning Glass (Kahn and Hershbein, 2018; Deming and Kahn, 2018; Javorcik et al., 2019), *indeed.com* (Mamertino and Sinclair, 2016; Turrell et al., 2019), *CareerBuilder.com* (Brown and Matsa, 2016; Marinescu, 2017), and *Snagajob.com* (Faberman and Kudlyak, 2016).

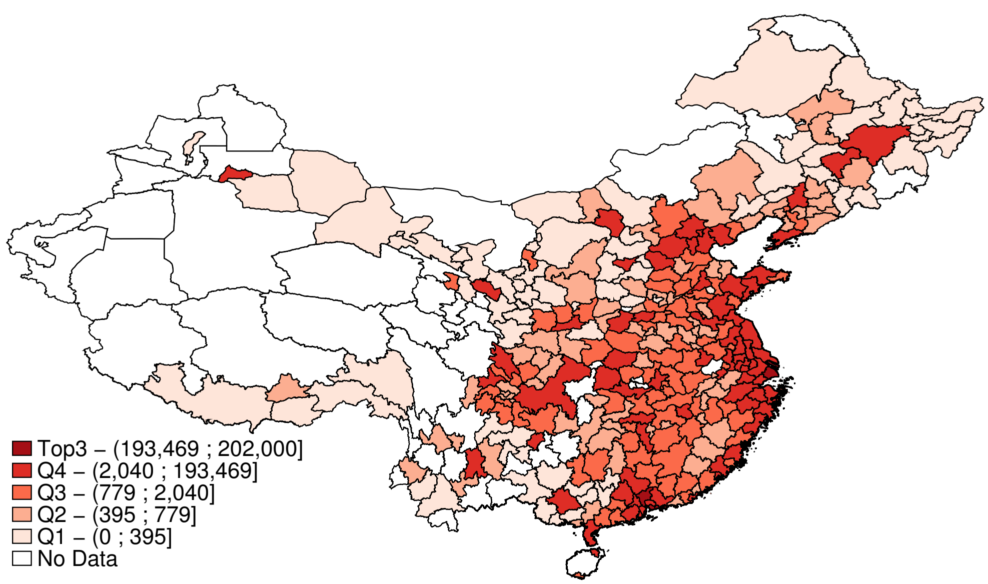
[7] Numbers presented for the years 2016-2018 range between 460,000 and 520,000 (see `https://ir.51job.com/ir/doc/2019/2018Form20FEDGARFINAL20190329.pdf`, page 28).

from 297 prefecture cities in 31 Chinese provinces.[8] We can further distinguish about 60 different industry sectors. Since tariffs are applied only on imports of physical products, we will mainly focus on job postings from a subset of these industries and neglect potential indirect effects through upstream or downstream propagation of the tariff shock. Overall, both manufacturing and non-manufacturing industries reveal a similar downward trend in their number of job postings towards the end of the year (see Figure A.3).

2.2 Representativeness of the data

In Figure 1 we illustrate the geographic coverage of our data on a map indicating the city-level administrative division. The relatively few and sometimes missing observations appear mostly in China's sparsely populated regions, while most of the revealed hiring activity takes place in Central and Eastern China. Indeed, the average incidence rate of unique job vacancy postings per month is highly correlated with city-level employment and GDP figures, as we show in Appendix Figure A.4.

Figure 1: Geographic coverage and concentration of job vacancies, full sample



Note: Authors' calculations based on data downloaded from 51job.com between May and November 2019. Figure shows coverage and concentration of average monthly number of observed vacancies across 297 out of 343 perfecture-level cities. Intervals depict quartiles.

Despite broad geographic coverage, online job-vacancy data comes at the expense of

[8] We refer to cities as the second layer of administrative division in China. The 31 provinces denote the first layer, which include four centrally-administrated municipalities (Beijing, Chongqing, Shanghai and Tianjin) and five autonomous regions (Guanxi, Inner Mongolia, Ningxia, Xinjiang, and Tibet).

potential limitations in their representativeness for the labor market. As discussed in related research, entry- and high-turnover jobs are likely to be over-represented and job ads posted online tend to require a higher educational background than traditional job boards (Davis et al., 2013; Kuhn and Shen, 2013; Kahn and Hershbein, 2018). By targeting young white-collar workers, 51job.com seems to share such characteristics. Examining the distribution of educational backgrounds in Figure A.5, we observe that more than 70 percent of the advertised jobs require college education as a minimum. While this is less than the 87 percent reported by Kuhn and Shen (2013, Table I), who used online job ads from *Zhaopin.com* in 2008-10, the China Population Census from 2015 and previous editions suggest a much lower share of 30 percent or less. Differences between searched skills in our data and matched skills in the Census data may explain part of this discrepancy, but, nevertheless, vacancies posted at 51job.com seem to disproportionately target higher skill segments of the labor market.

Regarding coverage and patterns across industries, we compare job postings to sectoral employment and firm populations.[9] Figure A.6(a) shows the number of jobs across industries, reflecting occupied jobs (i.e. employment) in the Census and job vacancies in our sample. The most salient group — manufacturing — coincides in both data sets, counting 45-50 percent of the jobs. The second and third largest numbers in our vacancy data belong to the health/pharmaceutical sector and to IT services. Neither of them stands out in the census data. Panel (b) of Figure A.6 presents the industry distribution of hiring firms. Again, the manufacturing sector dominates in both data sets while energy, health, real estate, and IT services follow in the vacancy data. In contrast to this, the census data prominently features public managements jobs and firms, which is not covered in our data. As in Kuhn and Shen (2013, Table A.1), online job ads appear to be skewed towards the private sector.[10]

2.3 Data sample

For our empirical analysis, we constrain our sample to firms that are directly involved in international trade, for reasons we explain in greater detail below. We use the company

[9]We use the most recent offical census data sets: the China Population Census 2015 and the China Economic Census 2018. More information can be found at *National Bureau of Statistics of China*. Different levels of sector and industry disaggregation complicate comparison of job-vacancy data with Census statistics and could lead to potential inaccuracies of this assessment. Numerical values should therefore be interpreted in orders of magnitude rather than precise values or cutoffs.

[10]See Table A.3 for further comparisons of our data to the information from the *Zhaopin.com* sample used in Kuhn and Shen (2013), and the selected urban census population from China's eight highest-income provinces summarized by the same authors.

name stated on 51job.com to find matching records in Chinese Customs statistics and obtain a sample of 30,123 firms which posted 607,532 different vacancies during the period from May through November 2019.[11]

Table 1: Summary Statistics of Job Vacancies from firms matched to customs data

Panel A. Job vacancy characteristics	Mean	Std.Dev.
Wage offer (10,000 RMB/year)		
Average	10.12	16.96
Minimum	8.01	13.08
Maximum	12.22	21.23
Non-wage compensation (share of vacancies)		
Subsidies	0.56	0.50
Bonus	0.49	0.50
Insurance package	0.71	0.45
Job requirements		
Average work experience (years)	1.76	1.99
Minimum	1.58	1.71
Maximum	1.95	2.28
College degree or higher (fraction of jobs)	0.77	0.42
Panel B. Firm characteristics	% of jobs	% of firms
Firm ownership		
State-owned/controlled	7.1	5.8
Foreign-owned	21.2	28.6
Private-domestic	71.5	65.5
Firm scale		
Small ($\leq$ 50 empl.)	5.8	19.0
Medium-small (50-500 empl.)	39.5	53.8
Medium-large (500-5,000 empl.)	39.6	22.8
Large (>5,000 empl.)	12.8	2.9
Number of unique jobs		607,532
Number of firms		30,123

Note: Author's calculations based on data collected from 51job.com. Summary statistics for sample of firms matched with China Customs information, May-November 2019. Reported percentages in Panel B might not add up to 100, because some firms did not report this information.

Table 1 presents summary statistics of our sample, where the average annual wage offer ranges around 100,000 RMB. This corresponds to about 14,500 US dollars per year, which is above China's average income per capita.[12] Many of the vacancies offer some form of non-wage compensation, such as subsidies and bonus payments. Over 70% of the

[11] As company names might be spelled differently across data sets, we require a similarity score of at least 75 percent to qualify as a match. On average firms in our final sample score close to 90 percent.

[12] GDP per capita for 2018-19 ranged just below 10,000 US dollars, which confirms that vacancies posted at 51job.com represent relatively better-paying jobs.

vacancies provide a package of five insurances and housing compensation as additional welfare benefits for employees.[13] In terms of job requirements, 77% of the vacancies require a college degree as a minimum, while the bar of working experience is set at 1.76 years on average (i.e., one year and 9 months). Panel B of Table 1 presents firm characteristics. We observe that privately owned domestic firms dominate the sample, followed by foreign-owned (and invested) enterprises and state-owned firms (SOEs).[14] Distinguishing firm scales indicates that large firms account for more than half of the job postings in our sample, while they represent only about 25 percent of the firms. Overall, medium-sized firms dominate, even though the very large and very small firms also provide meaningful numbers of observations.

We present further summary statistics in Appendix B. Figure B.2 depicts the geographic coverage of our matched sample, indicating the concentration of job ads as well as average wage levels. Not surprisingly, high-paying job offers concentrate in China's coastal provinces, besides some exceptions. In contrast to the overall sample, the number of vacancies for matched firms appears to be relatively higher the inner-land regions. An explanation could be that modern China has moved its labor-intensive manufacturing base into inner Chinese regions (Mau and Xu, 2019), whereas higher-paid jobs are offered in other, more knowledge-intensive sectors outside of our sample. In terms of sectoral coverage, we continue to observe a wide range of industries, but further concentration on manufacturing. Table B.1 shows that the top ten industries account for about two thirds of the observed job ads and firms in our sample and contain only one non-manufacturing sector: "Trade / Import and Export".[15] Monthly summary statistics for the number and key-attributes of the sampled job vacancies are shown in Table B.2. They indicate a gradual decline in hiring activity over time (including fewer firms posting job ads), but fairly stable compensation offers and job requirements on average.

In the following sections we describe how we exploit this data to infer the effects of the trade war in firms' hiring activity.

[13] Five insurances include unemployment insurance, endowment insurance, medical insurance, work-related injury insurance, and maternity insurance. Detailed descriptions are presented in Table B.4

[14] Comparing the respective percentages for jobs and firms further reveals that foreign-owned firms post relatively fewer job ads via this platform on average than Chinese firms.

[15] See Table B.6 for a full list of industries.

3 The US-China trade war

3.1 Stages of escalation

Since 2018, the US administration under President Trump implemented protectionist trade policies in several rounds using various justifications. In a first round, in February 2018, global safeguard tariffs were applied on imports of washing machines and solar panels. These were followed by tariffs on steel and aluminum in March 2018, justified with national security concerns. The new tariffs affected major US trading partners, who responded with retaliatory tariffs whenever they saw violations of WTO law (Bown and Kolb, 2019; Fajgelbaum et al., 2020).

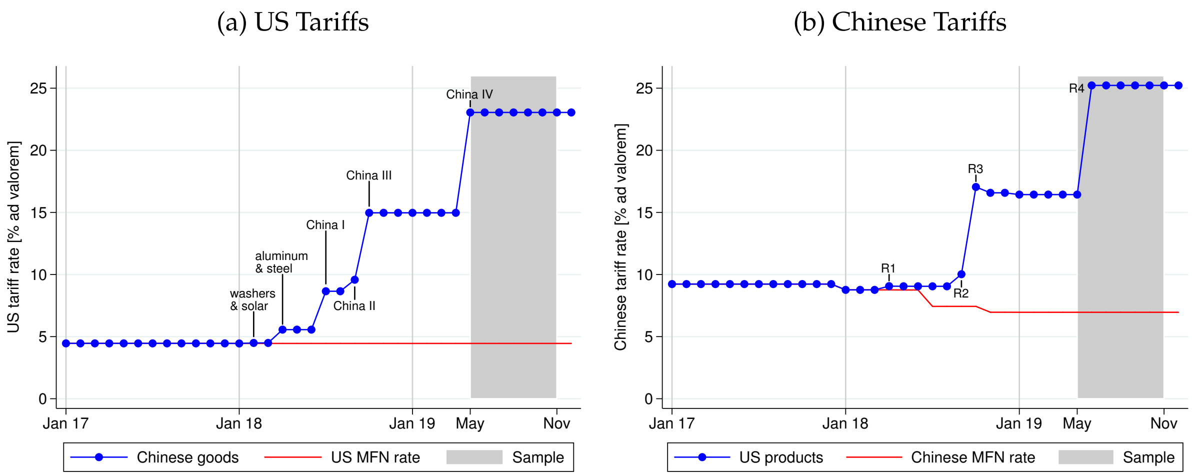
Next to these multilateral tariffs, China became a main target of US trade policy following investigations on the abuse of US companies' intellectual property rights and other allegations. Since then, the US government imposed additional tariffs on Chinese products in three rounds in early July, late August and late September 2018. A fourth round followed at the beginning of May 2019, which increased tariffs further on goods that were already targeted in the third round (China III). China retaliated by imposing own tariffs on US products, as shown in Figure 2. The additional bilateral tariffs contrast strongly with the average MFN tariffs the two countries apply on imports from most of its trade partners, in line with WTO guidelines.[16]

Next to their magnitude, tariffs were applied also to a broad range of products. The first major rounds of US tariffs on China became effective on July 06th and August 23rd, 2018, and targeted 891 and 244 product categories specified according to the 8-digit *Harmonized Tariff Schedule* (HTS), respectively, with an additional 25% increase on the existing rates. China's retaliation to these first rounds targeted an equivalent value of US goods and covered 184 and 173 products, respectively, with an extra 25% rate.[17] On September 24th, 2018, the US applied another 15% tariff rate on 4,626 products valuing about $200 billion in imports. China's response entailed a simultaneous tariff increase by 5 and 10 percentage points targeting 4,062 US products worth about $60 billion in imports. At the same time, the US administration announced to increase tariffs on the same goods by another 25 percentage points at a later stage and China announced to do the same. In fact, following a meeting in December 2018, the governments agreed to postpone these measures, and China eliminated some of its retaliatory tariffs on US cars and car parts in

[16] We do not exploit MFN tariffs in our empirical analysis, but display this information for illustrative purposes and assume that the majority of trade flows are subject to those (stable and predictable) rates.

[17] Earlier, in April 2018, China had imposed tariffs on 87 products amounting to $2.4 billion in imports from the US, responding to the steel and aluminum tariffs it had imposed on several of its trade partners.

Figure 2: Average US and Chinese Tariffs



Note: Authors' calculations based on data from Fajgelbaum et al. (2020), Li (2018), and own updates. Tariffs denote monthly averages computed from 8-digit Harmonized Tariff Schedules (HTS). Timing determined based on whether effective dates fell into first or second half of a month. R1-R4 indicate rounds of Chinese retaliation. Shaded areas indicate the observations period in our job-vacancy data (Section 2).

early 2019. However, another stage of the escalation followed in May 2019, when the US applied the previously announced additional tariffs. China followed a month later.

Despite ongoing threats over the months that followed, no further tariffs had been imposed since then. In December 2019, the two parties announced a so-called "Phase-one Deal" in which China committed to purchasing major amounts of US products, while leaving unchanged all other measures taken before. The agreement was signed in mid-January 2020 and came into effect a month later. As our sample with monthly job-vacancy data begins in May 2019, our analysis will focus on the last round of tariff increases, which are denoted by "China IV" and "R4" in Figure 2. At that stage the US had applied additional tariffs on almost 75 percent of the 8,225 products that are defined in the HTS.

3.2 Potential effects on firms' hiring behavior

Empirical research on the US-China trade war documents an abrupt and major impact of the tariffs on export revenues of the two countries (e.g. Fajgelbaum et al., 2020; Meinen et al., 2019). While Chinese exporters can theoretically pass on the tariffs to their US customers, it might be rational to absorb (at least some of) the burden to avoid excessive reductions in sales. To absorb the tariff burden, firms have to lower their "factory gate" prices, which can be achieved by lowering mark-ups or unit production costs. Regardless of which strategy a firm adopts, employees are likely to suffer. Lower sales translate into lower labor demand. Charging a lower price per unit sold might exert pressure on wages.

Our data does not allow us to trace adjustments for firms' existing employees. However, we do observe requested characteristics of firms' potential future employees. Given lower sales and the economic and political uncertainty surrounding the trade war, we expect that the number of job vacancies posted by firms facing additional US tariffs will decline (Handley, 2014; Handley and Limão, 2015; Benguria et al., 2020). We might also expect adjustments in the advertised compensation, if local labor market conditions allow for it. However, if wage offers decrease too much firms risk deterring good candidates. Reductions in the offered wage compensation may therefore require an increase in alternative forms of compensation, such as bonuses, subsidies or insurances.

Predicting adjustments in skill-requirements, such as education and previous work experience is more difficult. Skill demand might depend on firms' efforts of shifting sales towards products that are less exposed to US tariffs (Atkin, 2016; Blanchard and Olney, 2017). If such a strategy is relevant, we might observe relatively lower skill-requirements (e.g. educational background) in our job ads, as products shipped to the US belong to the most skill-intensive goods in China's exports (see Figure B.3 and B.4). An alternative channel could be that exposed firms respond to lower sales and cost pressure by seeking workers willing to accept lower wages. This might lead firms to request lower minimum standards in work experience and educational background in their job vacancies.

Since the trade-war involved reciprocally applied tariffs, Chinese firms might also be affected by the retaliation of their own government. These might theoretically protect some firms from external US competition, but it is questionable that this gives sufficient incentives for adjustments in labor demand and compensation offers. Given their ad-hoc nature, firms risk being exposed to a sudden removal of these tariffs, which would leave them with too many employees and potential separation costs adding to their earlier hiring costs. Indeed, related studies on the US labor market adjustments fail to provide any evidence of increased hiring and employment in protected industries and regions during this episode (Waugh, 2019; Goswami, 2020; Flaaen and Pierce, 2020).

Finally, since the goods China imports from the US might be important intermediate inputs, retaliatory tariffs might actually hurt importing firms or retailers as their supply-chains are disrupted.[18] Again, it is unclear how firms would respond: producing in-house and hire more; substitute import source and stay as before; or scale down and hire less. Derived adjustments in labor demand appear to depend critically on specific assumptions, so we intend to answer these questions empirically but remain skeptical

[18] Handley et al. (2020a) and Flaaen and Pierce (2020) find negative effects of such supply-chain disruptions on US firm and export performance.

regarding major increases in hiring activity after Chinese retaliation.

4 Empirical framework

4.1 Firm-level exposure to the trade war

4.1.1 Measurement and identification

We construct two measures of firm-level exposure to additional tariffs and discuss their interpretation. The first measure captures exposure to US tariffs, which mainly affects exporters. The second measure captures exposure to China's retaliatory tariffs on US products and mainly affects importers.

We denote $\text{Tariff}_f^{\text{US}}$ as the US-tariff exposure of firm f, which is constructed as follows:

$$\text{Tariff}_{ft}^{\text{US}} = \sum_{j \in J_f^e} \left[\frac{X_{fj0}^{\text{US}}}{\sum_i X_{fj0}^i} \tau_{jt}^{\text{US}} \right], \tag{1}$$

where τ_{jt}^{US} is good j's *ad valorem* tariff imposed by the US at time (i.e. month) t, X_{fj0}^{US} is firm f's exports of good j to the US in a pre-sample base-period $t = 0$ (i.e. 2016), which we divide by firms' total export revenues from good j, as indicated in the denominator. J_f^e is the set of goods exported by firm f. By interacting the US tariff rate with a measure of the relative importance of the US market for each exporter, we obtain our measure of exposure as a weighted average of the US tariff rate faced by firm f.

Likewise, based on China's retaliation tariffs on US goods and firms' imports data, we construct our measure of firm f's exposure to import tariffs:

$$\text{Tariff}_{ft}^{\text{CHN}} = \sum_{j \in J_f^m} \left[\frac{M_{fj0}^{\text{US}}}{\sum_i M_{fj0}^i} \tau_{jt}^{\text{CHN}} \right], \tag{2}$$

where τ_{jt}^{CHN} is good j's *ad valorem* tariff imposed by China on the US goods at time t (i.e. month), M_{fj0}^{US} is firm f's average imports of good j from the US in a pre-sample base-period $t = 0$ (i.e. 2016), which we divide by firms' total imports of good j, as indicated in the denominator. J_f^m is the set of goods imported by firm f. By interacting the Chinese tariff rate on US products with a measure of their relative importance for each importer, we obtain our firm-level measure of exposure to import tariffs.

Since we can directly observe US and Chinese applied tariffs, as well as firms' relative "specialization" in US trade relations, our measure denotes an accurate quantification of tariff exposure. Indeed, our approach is similar to related research that studied the impact of the trade war on local US labor markets (e.g. Waugh, 2019; Goswami, 2020). Furthermore, by employing customs data from 2016 to construct our pre-period weights, we are able to address endogeneity concerns that could potentially bias our estimates.[19] However, we also face one caveat for identification, as our pre-sample period weight does not take into account firms' domestic sales and purchases. As a result, it is possible that a firm with a high degree of specialization in US trade relations, according to our measure, is actually specialized in domestic transactions. We would overstate the degree of such a firms' exposure and may likewise understate the exposure of highly export-oriented firms. Although we cannot rule out such a possibility, we expect that such measurement error would lead to an attenuation bias and loss of precision in our point estimates.

4.1.2 Tariff and trade data

To construct our measures of firm-level exposure, we combine information from two datasets. The first is the China Customs dataset, in which we observe export and import values at the product-firm-destination (or source) country level for all international transactions in 2016. We use this information to compute the firm-specific weights that capture their relative reliance on US trade relations. We combine this data with a detailed dataset of US tariffs imposed upon China, as well as Chinese retaliatory tariffs on the US, which is reported at a monthly frequency for the years 2016-2019. We collected the reciprocal Chinese and US tariffs from several data sources, including official communications by the US Trade Representative, the CARD Trade War Tariffs Database (Li, 2018), as well as data provided by Fajgelbaum et al. (2020) and Bown and Kolb (2019). US and Chinese MFN tariff rates were collected from the WTO (World Trade Organization) *Tariff Download Facility* database. Chinese MFN tariffs were further complemented with data from Bown and Kolb (2019), which includes more recent changes in tariffs based on official government communications.

The evolution of these tariffs has already been discussed in Section 3, Figure 2, and we provide further details for the period 2018-2019 in Table B.3. Columns (1)-(4) show that, starting with MFN tariff rates of 3.6% and 9.2% in an average (6-digit HS) product category, both the US and China increased their reciprocally bilateral discriminatory tariffs up to 23.2% and 25.1% respectively in just two years. Columns (5)-(8) indicate increases

[19] Note that the year of 2016 pre-date the years of Donald Trump's presidency. Although he threatened to impose new trade policy measures against China already during his electoral campaign, his victory in late 2016 was a surprising outcome that is unlikely to have driven anticipatory behavior among Chinese firms. See Amiti et al. (2019) for further discussion on this issue. Also note that any major anticipation effects in firms' hiring behavior would induce a downward bias on our estimated coefficients.

in very similar orders of magnitude for our firm-level measure of tariff exposure obtained from Equations (1) and (2). The period since May 2019 is of central interest for our study, where we observe an average increase in firm-level US tariff exposure by about 7.8 percentage points (i.e., from 0.169 to 0.247 in column (5)). Firm-level exposure to retaliatory tariffs increased by about 7.0 percentage points (i.e., from 0.136 to 0.206 in column (7)).

4.2 Estimation

4.2.1 Empirical baseline specification

To investigate the effect of tariffs on firms' recruiting behavior, we adopt a simple linear panel regression model:

$$y_{ft} = \beta_1 \ln(1 + \text{Tariff}^{\text{US}}_{f,t-1}) + \beta_2 \ln(1 + \text{Tariff}^{\text{CHN}}_{f,t-1}) + \mathbb{X}'_{ct}\gamma + \eta_f + \eta_t + \varepsilon_{ft}, \tag{3}$$

where $\text{Tariff}^{\text{US}}_{f,t-1}$ and $\text{Tariff}^{\text{CHN}}_{f,t-1}$ are US and Chinese tariffs faced by firm f, lagged by one month. We employ lagged tariff exposure since we count vacancies as monthly totals, while actual implementation and responses could have taken place on different dates during the same month. By using lags, we avoid potential problems arising from a different order of events and also allow firms a limited amount of time to adjust to the tariffs.[20] In line with the empirical trade literature we employ tariff exposure as an iceberg trade-cost term by adding one to the tariff rate and taking logs (e.g., a 5 percent of firm tariff exposure measure would enter the equation as $\ln(1.05)$). Overall, the estimated coefficients β_1 and β_2 will indicate the average treatment effect of the final round in the US-China trade war that reveals throughout our 5 months of observations.

To isolate the effect as good as possible, we control for potentially confounding factors and implement firm fixed effects (η_f) and time fixed effects (η_t) into our baseline estimation equation. Time fixed effects control for aggregate trends or shocks that are correlated with both our dependent variable and our main variables of interest. This includes, for example, seasonal fluctuations in hiring which might happen to coincide with tariff changes. Firm fixed effects are included to control for unobservable time-invariant characteristics of a firm. This is of particular importance in our context, as we do not observe many firm-level characteristics, including its hiring history. However, as we can observe firms' location (at the city level c), we employ time-varying control variables along these dimensions in vector $\mathbb{X}_{ct}$ to capture aggregate developments in local labor markets.

[20] Meinen et al. (2019) show that the effects of the trade war on US imports from China started to materialize in the last quarter of 2018, i.e. in the quarter after the first tariffs had come into effect. This is also in line with our descriptive evidence presented in Figure B.1.

Specifically, we include the total number of firms posting job vacancies as well as the total number of job vacancies available in city c and at time t.[21] Finally, ε_{ft} denotes an i.i.d. error term which we cluster at the city-month level. As an alternative to our baseline specification, we also estimate a model with firm (η_f), city-time (η_{ct}), and industry-time (η_{jt}) fixed effects to control for distinct seasonality patterns along those dimensions.

4.2.2 Dependent variables

We employ a number of different dependent variables, y_{ft}, to analyze alternative outcomes of the US-China trade war. The primary outcome of interest, however, is the number of job vacancies posted by a firm. Such job ads denote the "extensive margin" of firms' hiring activity and we consider two ways of measuring it. First, we measure the *stock* of job ads held by a firm in a particular month. That is, if a firm posts a job in May and it is still online in June and July, it will be counted into our measure of active job postings. A caveat arises when we want to interpret any changes in this variable, due to our inability to observe why a job ad disappears. This can be due to a successful match or due to a withdrawal that resulted from changed hiring decisions. We therefore also consider the *flow* of newly posted vacancies. With this measure, each job ad is counted only once, and a vacancy is considered as being new, whenever it could be observed at download instance t but not at the previous instance $t-1$. A change in this measure might give a clearer indication of the firm's hiring activity.

Next to counting the number of online job vacancies, we are also interested in the content of the job ads. We analyze these by observing (i) measures of the nominal wage offered in a firms' average job-ad; (ii) indicators of other forms of compensation, such as bonus payments, subsidies or insurances; and (iii) job requirements, as specified by previous work experience and educational background. A detailed overview of the variables along with further descriptions is provided in Table B.4. Since these measures relate to the "intensive margin" of the job ads, we take into account the possibility (and practice) of firms to update their existing vacancies over time. We therefore compute firm-level averages of these variables based on the stock of active vacancies in a particular month.

4.2.3 Sample structure

As indicated in Section 2, we analyze the impact of the trade war on the hiring behavior for a subpopulation of firms that are engaged in international trade. The reasons for

[21] Since every firm f resides only in a single location, we suppress city subscripts c in our dependent variable and in the tariff measures to avoid confusion about the dimensions of their variation.

doing so are threefold. First, many firms in our job-vacancy data might be unaffected by the trade war, simply because they do not engage in international trade (directly or indirectly). Second, even if they are affected indirectly, it is impossible for us to measure their exposure to the trade war, as we do not observe such information.[22] Third, since typically only a fraction of firms in a country are involved in international transactions, and as such firms are quite distinct from non-trading firms, we do not believe that non-trading firms constitute an appropriate control group.[23] Instead, our control group comprises an abundant number of firms that trade internationally but not with the US. For those firms Tariff_{ft}^{US} and Tariff_{ft}^{CHN} are equal to zero by construction and they count about a third of the firms in our sample. Likewise, we observe about equally-sized groups of firms which are exposed to the trade war through only one channel: either via their exports or via their imports. Overall, about half of the firms in our sample are exposed to the additional tariffs imposed during the most recent round of the trade war, while the remaining firms do trade with the US but were not affected by these tariffs.[24]

Table B.5 provides further information on the variation in our sample. It shows summary statistics for average vacancy stocks, wage offers, and firm characteristics by sub-samples of firms with varying lengths of posting job ads.[25] Not only does the number of firms differ across these sub-samples, characteristics such as the number of vacancies posted, average wage and scale of firms also vary. Both the number of job vacancies and average wages have an upward trend as the duration of job posting increases. Firms with larger numbers of employees are more likely to continuously post job-ads, while small-scale firms post jobs for a shorter duration. This suggests that larger firms also offer better paid jobs on average. Ownership types of firms posting jobs across months are relatively stable across posting lengths. Overall, our data appears to feature sufficient within- and across-firm variation to exploit for the purposes of this study.

[22] Also the reported (more aggregated) industry affiliations cannot be directly translated into firm exposure via input-output linkages as done, for instance, by Flaaen and Pierce (2020). This has implications for the interpretation of our results as we explain in our concluding remarks below.

[23] One reason for this skepticism is differences in firm size that typically prevail between trading and non-trading firms. Another reason is the different market environments in which such firms operate. While trading firms operate at a global scale in highly competitive markets, non-trading firms may be shielded from such competition if they produce and sell exclusively in domestic (niche) markets.

[24] In our robustness check below, we report results for firms' overall hiring activity based on alternative compositions of our control group.

[25] In the first panel, *1-month firms*, corresponds to summary statistics for firms that post job ads in only one of the seven months we observe in our sample, while the next panel, *2-month firms*, features firms posting jobs for two months, and so on.

5 Results

5.1 Main findings

5.1.1 Number of job vacancies

Our first dependent variable measures the absolute number of job vacancies posted by firm f at time t. Since this is a count variable which features zeros and otherwise discrete positive values, we present results for a linear regression approach, as introduced in the previous section, and for a Poisson regression model (Wooldridge, 2010; Marinescu and Rathelot, 2018).

Table 2: Number of vacancy postings and exposure to tariffs

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Stock (all job vacancies)			Flow (new job vacancies)		
Number of vacancies (N^v_{ft})	OLS	OLS	Poisson	OLS	OLS	Poisson
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	-3.219	-3.247	0.270	-7.725**	-7.567**	0.176
	(2.575)	(2.820)	(0.356)	(2.300)	(2.346)	(0.471)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	-3.322**	-4.200**	-0.492**	-2.190*	-6.265***	-0.651**
	(1.145)	(1.582)	(0.224)	(1.112)	(1.348)	(0.311)
Observations	189,272	188,909	188,705	189,196	188,880	188,479
R-squared	0.763	0.767		0.522	0.536	
City Controls	Y			Y		
Month FE	Y			Y		
Firm FE	Y	Y	Y	Y	Y	Y
City-Month FE		Y	Y		Y	Y
Sector-Month FE		Y	Y		Y	Y

Notes: Regressions use firm online job vacancy data from May through November 2019. Results in column (1)-(3) are based on the stock of firms' job vacancies, where job ads are counted independently across months. Results in column (4)-(6) are based on flow of new job vacancies, where only the first appearance of each job ID is counted. Time-varying city-level control variables include the total number of firms and vacancies observed. Standard errors are reported in parentheses. For linear models, estimated coefficients denote semi-elasticities and standard errors are adjusted for clustering at the city and month level. For the Poisson fixed-effects models, coefficients reflect estimated elasticities and reported standard errors are bootstrapped. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2 displays the results for the stock and flow of firms' job postings, respectively, in columns (1)-(3) and (4)-(6). Throughout all specifications, we find a negative and statistically significant effect of increasing US tariffs on job postings of exposed firms. Including city- and sector-month fixed effects into our model results in quantitatively larger coefficient estimates, as shown in columns (1)-(2) and (4)-(5). Also the Poisson model suggests that firms that exported to the US reduced hiring efforts when facing increased tariffs. Generally, this effect reveals stronger when we measure the flow of job vacancies, which implies that exposed firms advertise fewer new jobs.

To give these coefficients a quantitative interpretation, we consider the result from column (2) to infer that a one log-point increase in $\ln(1 + \text{Tariff}^{US}_{ft-1})$ results in 4.2 fewer job vacancies on average per firm. In fact, using numbers from Table B.3, we see that this variable increased by about 0.065 log points during our sample period. This implies about 0.27 fewer jobs offers by an average firm between May and November 2019. As we observe about 20,500 firms at the beginning of our sample, the estimated job loss amounts to approximately 5,600 fewer job postings in total. In relative terms, we observe in Table B.2 that an average firm posted about 11.34 job ads at the beginning of our sample period, so that the estimated 0.27 fewer jobs per firm correspond to a reduction by 2.4 percent. Our Poisson results, displayed in column (3), suggest a similar reduction by (0.492×0.065≈) 3.2 percent.

In contrast to the US tariffs, coefficients estimated for the effect of China's retaliation are less robust. The linear models result in negative coefficient estimates, which are statistically significant only for the new job ads in columns (4) and (5). This would point towards a detrimental effect of Chinese retaliation tariffs on firms' scale of activity, which results in less hiring. However, the Poisson model suggests the opposite when it reports a positive (albeit statistically insignificant) coefficient, which would point towards an increased hiring activity. Overall, the average treatment effect of China's retaliation on firms' hiring activity remains inconclusive.

5.1.2 Average Wage per Vacancy

We next study how firms' wage schedules responded to the tariff changes. To do so, we compute for each firm f the average wage w_{ft} offered in the vacancies it had posted at time t. Since job ads (v) typically indicate a wage range, i.e. a minimum and a maximum wage (or salary) level, we analyze responses in both of these wages separately and in addition responses in the average of the two ($w^{mean}_{fvt} \equiv (w^{\min}_{fvt} + w^{\max}_{fvt})/2$). In all specifications, we measure wage rates in logs.

Table 3 presents our results. We find small positive, yet statistically insignificant, responses to Chinese retaliation tariffs, and negative statistically significant coefficients for the effect of US tariffs on advertised wage levels. Columns (1) and (2) suggest that the lower bound of annual wages offered in our observed job ads decreased among firms that were more exposed to the trade war. The same can be found for the upper bound of

Table 3: Wage offers and exposure to tariffs

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wage/salary ($\ln w_{ft}$)	Minimum		Maximum		Average		Dispersion	
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	0.009	-0.002	0.035	0.022	0.026	0.014	0.026	0.025
	(0.044)	(0.045)	(0.046)	(0.048)	(0.045)	(0.046)	(0.015)	(0.017)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	-0.085**	-0.083*	-0.073*	-0.065*	-0.077*	-0.071*	0.013	0.018
	(0.034)	(0.042)	(0.031)	(0.038)	(0.032)	(0.039)	(0.011)	(0.012)
Observations	107,800	107,448	107,800	107,448	107,800	107,448	107,800	107,448
R-squared	0.738	0.742	0.732	0.736	0.734	0.738	0.736	0.740
City Controls	Y		Y		Y		Y	
Month FE	Y		Y		Y		Y	
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
City-Month FE		Y		Y		Y		Y
Sector-Month FE		Y		Y		Y		Y

Notes: Regressions use firm online job vacancy data from May through November 2019. Average wages in columns (1) to (6) are measured in logs ($\ln w_{ft}$); wage dispersion in columns (7) and (8) is measured as ($\ln w^{max}_{ft} - \ln w^{min}_{ft}$). Coefficients report estimated wage-tariff elasticities. Time-varying city-level control variables include the total number of firms and vacancies observed. Standard errors are reported in parentheses and adjusted for clustering at the city and month level. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

annual wages and for the average of the two, in columns (3)-(4) and (5)-(6), respectively. Throughout, the estimated coefficients suggest a fairly low elasticity of wages with respect to faced tariffs among Chinese firms. Yet, given the major increase in tariff levels during the trade war, the coefficients imply about $((\ln([1.247]) - \ln[1.169]) \times \hat{\beta}_1) \approx 0.5$ percent lower wages offered by affected firms (which corresponds to about $70 less per year, if the average wage compensation is $14,500 as stated in Table 1).[26] The last two columns confirm that the size of the indicated wage intervals does not change significantly among firms.

5.1.3 Non-wage compensation

A lower offered wage does not necessarily imply the labor costs would decrease. Non-wage compensation can account for major portions of total labor costs (Woodbury, 1983; Liu et al., 2019). Indeed, it might be convenient for firms to offer alternative forms of compensation if they have different means to providing such benefits. To evaluate such

[26] Since job postings quote nominal wages, the income loss in purchasing power adjusted terms is likely to be higher, given overall lower price levels in China compared to high income economies. For example, according to World Bank data, China's PPP-adjusted GDP per capita is about 50 percent higher than the nominal figure.

adjustments, we focus on three different forms of alternative compensation schemes: bonuses, subsidies, and insurances. With bonuses firms can avoid early commitments to paying higher wages when the actual performance of the future employee (but also of the firm as a whole during the trade war) is uncertain. Subsidies include the provision of overtime pay or transportation, communication, and meal allowances by the employer, whereas insurances include the provision of a "five-insurances" package that is part of China's social security system.[27]

To evaluate whether firms increasingly advertise the provision of such alternative forms of compensation, we compute the share of a firm's job ads including such components. That is, the share of jobs offering bonus payments to employees ($Share_{ft}^{Bonus}$) is defined as follows:

$$Share_{ft}^{Bonus} = \frac{\sum_{v \in \Omega_{ft}} \mathbf{1}_{fvt}(\text{the advertisement explicitly offers bonus})}{N_{ft}^{v}} \tag{4}$$

where Ω_{ft} denotes the mass of all vacancies posted by firm f in month t, N_{ft}^{v} is the number of job vacancies posted by firm f in month t, and $\mathbf{1}_{fvt}$ is an indicator variable that equals to one if job-ad v explicitly mentions that the job will be offered with performance-based bonus payment. We compute shares of jobs offering subsidies, $Share_{ft}^{Sub}$, and insurances, $Share_{ft}^{Ins}$, in the same fashion.

Table 4 reports our results. Using our baseline specification, we find that firms exposed to higher US tariffs increasingly advertise bonus payments and subsidies as a form of non-wage compensation. This would be in line with earlier conjectures that such payment schemes offer greater flexibility to employers, while providing adequate incentives for qualified candidates to apply (Luft, 1994). However, as we turn to our more demanding specification, including city- and sector-specific time effects, point estimates become smaller and loose statistical significance. About half of the originally estimated effect can be attributed to general industry-level dynamics.[28] This suggests that sectors where relatively more US-tariff exposed firms operate have been experiencing a general trend in moving towards increased non-wage compensation schemes, and that potential responses due to the trade war are statistically indistinguishable from this trend.

Considering the corresponding coefficients for China's retaliation tariffs, we find sim-

[27] The five insurances include unemployment, pension, medical, work-related injury, and maternity insurances. While being mandatory in principle, it is not implemented throughout the country and some foreign enterprises might be eligible for exemptions from it. See www.china-briefing.com/news/social-insurance for an overview.

[28] We experimented with different combinations of fixed effects and found that downward correction of point estimates and loss of statistical significance arises from the inclusion of sector-month fixed effects.

Table 4: Non-wage compensation and exposure to tariffs

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Share of vacancies offering	Bonuses		Subsidies		Insurances	
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	0.051*	0.063*	0.012	0.005	0.016	0.024
	(0.026)	(0.027)	(0.044)	(0.046)	(0.026)	(0.025)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	0.050**	0.025	0.046**	0.022	0.016	0.010
	(0.017)	(0.017)	(0.017)	(0.014)	(0.020)	(0.020)
Observations	107,800	107,442	107,800	107,442	107,800	107,442
R-squared	0.855	0.857	0.863	0.865	0.864	0.866
City Control	Y		Y		Y	
Month FE	Y		Y		Y	
Firm FE	Y	Y	Y	Y	Y	Y
City-Month FE		Y		Y		Y
Sector-Month FE		Y		Y		Y

Notes: Regressions use firm online job vacancy data from May through November 2019. Dependent variables denote fractions, coefficients report estimated semi-elasticities. Time-varying city-level controls include total number of firms and vacancies observed. Standard errors are reported in parentheses and adjusted for clustering at the city and month level. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

ilar results in terms of signs, but differences in magnitudes and precision. Coefficients for subsidies, in columns (3) and (4), are quantitatively small and statistically insignificant. The same is true for the share of vacancies offering insurances, where neither US nor Chinese tariffs appear to have affected such policies. In terms of bonus payments, however, we find a robust positive and statistically significant effect of Chinese retaliation in the trade war, which is suggestive of a shift towards performance-based compensation among exposed firms. Although none of our previous indicators revealed a clear systematic response by firms to retaliatory tariffs, the positive signs for wages, vacancy postings (using Poisson estimators) and those presented here (in columns (1) and (2) of Table 4) might be suggestive of a slight increase in labor demand among firms that attempt to substitute imports from the US. Overall, the empirical evidence for an average treatment effect on offering non-wage compensation components is mixed.

5.1.4 Job requirement

Besides adjustments in offered employee compensation, we are also interested in potentially changing job requirements, which might point towards a shifting scope of activities among exposed firms. Indeed, changes in wages and in the number of posted vacancies could be associated with changes in job requirements. Deming and Kahn (2018), for example, document a positive correlation between average wages offered and the required number of years of schooling. As we found fewer job offers overall, as well as slightly lower wage compensation in our data, we might expect that also the required educational background will be lower.

Like in the previous subsection, we analyze effects on firms' job requirements by measuring the fraction of a firm's vacancies that explicitly require applicants to have a college degree (or higher):

$$Share_{ft}^{College} = \frac{\sum_{v \in \Omega_{ft}} \mathbf{1}_{fvt}(\text{the advertisement explicitely require college degree})}{N_{ft}^{v}} \tag{5}$$

where Ω_{ft} denotes the mass of all vacancies posted by firm f in month t, N_{ft}^{v} is the number of job vacancies posted by firm f in month t and $\mathbf{1}_{fvt}$ is an indicator variable that equals to one if the advertisement v explicitly mention that the qualified applicants will require a college degree. Next to educational background requirements, firms might also adjust requirements regarding previous work experience (Cai and Stoyanov, 2016). We therefore construct corresponding measures for the lower and upper bounds of requested working experience (measured in years), as well as their average.

Table 5: Job requirements and exposure to tariffs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Previous work experience (in years)						College degree	
	Minimum		Maximum		Average		Fraction	
$\ln(1 + \text{Tariff}_{ft-1}^{\text{CHN}})$	0.006	0.022	-0.024	-0.007	-0.009	0.008	0.027	0.023
	(0.095)	(0.121)	(0.135)	(0.171)	(0.114)	(0.145)	(0.038)	(0.035)
$\ln(1 + \text{Tariff}_{ft-1}^{\text{US}})$	-0.067	0.018	-0.067	0.040	-0.067	0.029	-0.070**	-0.043*
	(0.055)	(0.071)	(0.082)	(0.102)	(0.068)	(0.086)	(0.021)	(0.022)
Observations	107,544	107,181	107,544	107,181	107,544	107,181	107,800	107,437
R-squared	0.745	0.748	0.744	0.748	0.745	0.749	0.712	0.716
City Control	Y		Y		Y		Y	
Month FE	Y		Y		Y		Y	
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
City-Month FE		Y		Y		Y		Y
Sector-Month FE		Y		Y		Y		Y

Notes: Regressions use firm online job vacancy data from May through November 2019. Dependent variables denote number of years in columns (1)-(6) and fractions in columns (7)-(8); coefficients report estimated semi-elasticities. Time-varying city-level controls include total number of firms and vacancies observed. Standard errors are reported in parentheses and adjusted for clustering at the city and month level. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

The results are reported in Table 5, where columns (1)-(6) suggest that neither US nor Chinese tariffs had any systematic impact on required working experience. However, we observe in column (7) and (8) that firms exposed to US tariffs significantly decreased the fraction of job ads requiring a college degree. In contrast to this, we obtain positive (but again statistically insignificant) coefficients for the effect of China's retaliation on education background requirements in firms' vacancy postings. The decrease in educational background requirements among US-tariff exposed firms is consistent with the reported decrease in average wage offers and potentially results from a compositional effect as firms scale down on their relatively more exposed skill-intensive goods (see Figure B.3).[29]

Altogether, our findings suggest that the US-China trade war had a mostly one-sided impact on the labor demand and hiring behavior of Chinese firms that were directly exposed to higher tariffs. While exporters facing higher US tariffs reveal lower labor demand, wages and skill demand (as well as a tendency to adopt more flexible and non-wage compensation schemes), importing firms' adjustments are less clear-cut.

5.2 Robustness checks

In this subsection, we scrutinize the robustness of our findings by addressing potential concerns regarding our identification.

5.2.1 Placebo experiment with randomly assigned tariff exposures

For our first robustness check, we perform a placebo experiment in which we randomly assign Chinese and US tariff exposure to firms. The purpose of doing this is to test how likely it is that our baseline findings reflect coincidental correlations.[30] By assigning tariff exposure randomly to firms in our sample, we expect our earlier findings to disappear if the envisaged mechanism is correctly identified.

Hence, firm f's "fictional" tariff exposure can be written as:

$$\widetilde{\text{Tariff}}_{f,t}^{\text{Type}} = \text{Tariff}_{s,t}^{\text{Type}}, \qquad \text{Type} \in \{\text{US}, \text{CHN}\}, \tag{6}$$

where s indexes a firm that is randomly drawn from our original estimation sample. That is, f adopts the level of exposure we actually for firm s, which we draw randomly from our sample. We repeat the above procedure 30 times to obtain a bootstrapped "fictional" sample and carry out our previous analysis once again. The results are reported in Appendix Tables C.2-C.5. None of our previously significant estimates can be reproduced in

[29]Indeed, we find that the decrease in wage offers due to US tariffs is partially explained by a lower fraction of jobs requiring a college degree. We report the corresponding regression results in Table C.1.

[30]A similar placebo test has been employed by Beverelli et al. (2017) to study the effect of restriction on service trade.

our placebo estimation, which supports our baseline results and their economic interpretation.

5.2.2 Control for pre-trends

Our second robustness check concerns our short sample period. With tariffs entering into force in May and June 2019, and using a one-period lag, we can barely control for pre-trends. This may cast doubts about the existence of a causal relationship between our outcome variables and firms' tariff exposure. In fact, firms' trade structure might be correlated with underlying factors that determine differential trends in labor demand while being unrelated to the trade war. We attempt to address this concern by drawing on information from the Annual Survey of Industrial Production (ASIP), which allows us to observe *actual* employment and average wages paid for a subset of our firms in the years 2012-2013; long before the trade war.[31] Inference relies on a falsification test in which we estimate the observed firm-level change in (log) employment and (log) average wage payments between 2012 and 2013. A statistically significant coefficients for our measures of tariff exposure would suggest a potentially underlying long-term trend in our data and challenge our identification.

Table C.6 presents the results for realized employment in columns (1)-(4) and for average realized wages in columns (5)-(8), using different combinations of fixed effects and controls. Without any fixed effects or firm-level controls, we find systematically higher employment growth among US-tariff exposed firms and slower wage increases. Estimated coefficients are corrected downwards and lose statistical significance as soon as we include industry fixed effects, city fixed effects or firm-level control variables (i.e. total sales). Exposure to Chinese retaliation tariffs reveals statistically insignificant results throughout and with opposite signs. Compared to our main results, historical employment among exposed firms appears to have followed a different trend, which lends some confidence to our identification strategy. The results are somewhat less conclusive for historical wage growth, where coefficients reveal the same sign but statistical significance is considerably weaker.

5.2.3 Timing of the effects

Instead of considering historical employment and wage growth for a subset of firms, we might infer validity also by looking at the timing of the estimated effects. The most

[31]The ASIP is conducted by the National Bureau of Statistics of China. The survey includes manufacturing sector firms whose revenue is more than five million RMB each year. We are able to match 4,669 firms based on their reported company name and location.

intuitive assumption would be to expect adjustments to occur immediately or at least soon after newly imposed tariffs apply. Later adjustments should be weaker. However, if our estimated coefficients capture an underlying pre-trend, we should observe fairly similar effects at different instances in our sample.

In Table C.7, we include deeper lags of tariff exposure into our regression for the number of job vacancies posted by firms. Estimated responses to China's retaliatory tariffs remain fairly fragile and inconsistent across specifications, like in our main findings. Additional US tariffs appear to have mainly immediate effects and weaker (and less consistent) effects in later periods. Tables C.8-C.11 further support this finding, suggesting that deeper lags of tariffs alone are statistically insignificant for most of our outcome variables, and considerably smaller and less significant for the number of vacancies.

5.2.4 Alternative control groups

We scrutinize identification further by considering alternative control groups. Our original sample pools different groups of firms, including those that did not sell to or source from the US at all (henceforth, Group 1, being unexposed by definition) and those that traded with the US, but not in goods targeted by China III/IV tariffs (Group 2). The former counts 7,676 firms in our estimation sample and should facilitate better identification than the latter, which counts only 1,213 firms. Group 2 can be viewed as being exposed to a higher tariff *risk*, and hence more similar to the treatment group, given its trade linkages with the US, potential treatment in earlier rounds (China I and II) and the surrounding trade policy uncertainty (e.g. Benguria et al., 2020).[32]

When we re-estimate our main specifications on vacancy postings considering the respective control groups separately, we find that reductions in the number of job ads are quantitatively and statistically more pronounced relative to Group 1. In fact, as shown in columns (3)-(4) of Table C.12, the estimated semi-elasticity of new vacancy postings with respect to US tariff increases is almost twice as high relative to Group 1 than for Group 2. Also responses to retaliation tariffs appear to be more pronounced relative to the non-exposed set of firms that never traded with the US in the base-year 2016. The fact that results remain statistically significant even when we keep control Group 1 out of our sample suggests that identification operates also via the product-mix of firms' imports and exports, which results in differential degrees of exposure to tariffs.

[32]The treatment group comprises 12,600 firms in our sample, so that the overall population amounts to 21,489 firms. This number results from the fact that some firms have only one (or few) observations in total during the sample period, so that the inclusion of fixed effects results in perfectly collinearity and removal from the sample.

We conclude from this subsection that firm-level adjustments in the number of vacancy postings (i.e. labor demand) can be interpreted as causally related to tariff increases experienced during the trade war. Adjustments in other dimensions have been generally more fragile, making rigorous causal inference more difficult.

5.3 Firm heterogeneity

So far, our results revealed the estimated average tariff effects and we have not paid much attention to potentially heterogeneous responses across firms. To explore this, we consider two main dimensions of firm heterogeneity in this subsection, distinguishing their size (as revealed from the aggregated trade volume in our base-year 2016) and their ownership (as revealed from the firm-level information provided via the online job portal 51job.com). We also consider potentially heterogeneous responses between firms with different trade baskets in terms of product range and characteristics.

5.3.1 Firm size

Based on their observed trade volumes in 2016 (i.e., exports plus imports), we divide firms into three equally-sized groups: small, medium and large. For each of these subsamples, we re-run our main specifications and report the obtained point estimates with corresponding 95% confidence intervals graphically.[33]

Figure C.1 presents estimates for labor demand, as measured by their total number of job vacancy postings. Responses to higher US tariffs are displayed on the left, while adjustments to Chinese tariffs are shown on the right. Panel (a) reports the semi-elasticities obtained from our linear panel specification, while Panel (b) reports estimated elasticities obtained from the Poisson model. Figure C.2 reports findings for changes in offered wages among firms' job ads, while Figures C.3 and C.4 focus on the different forms of non-wage compensation and advertised job-prerequisites, respectively.

We find that large firms tend to be the least responsive to any kind of tariff and in terms of most outcome variables. In some cases, large confidence intervals suggest heterogeneity even within this group, but point estimates for the number of vacancy postings or advertised wage offers are typically closer to zero than for other firms. A tendency towards increasing number of job postings offering bonus payments and employee subsidies can be observed for these firms, as well as a modest increase in educational requirements

[33] In our sample periods (i.e., May to November of 2019), the average exposure to US tariffs for small-, medium-, and large-size firms are 0.03, 0.09 and 0.13, respectively; the average exposure to China's tariffs for small-, medium-, and large-size firms are 0.04, 0.06 and 0.10, respectively.

when facing US tariffs. This contrasts with the findings for other firms and also with average effect found for the pooled sample above.

Concerning small firms, we find this group to be the most diverse, given the large confidence intervals. While point estimates indicate substantial downward adjustments in job postings, wage offers, subsidy offers and job pre-requisites (following US tariff increases), they rarely pass the 5% significance threshold. Adjustments are typically more modest and less precisely estimated in the case of Chinese retaliatory tariffs. Despite their within-group heterogeneity, however, they seem to contribute to the robust results reported for adjustments to US tariffs in terms of labor demand, wage offers and educational background requirements.

Medium-sized firms constitute the group with the clearest results overall. They appear to scale down, offer lower wages, and request less educational background (and to some extent working experience) when facing additional US tariffs. Non-wage compensation tends to increase most significantly in terms of subsidies and modestly in terms of offering bonus payments (like most other firms). Interestingly, when affected by Chinese retaliatory tariffs, these firms appear to increase efforts to attract more educated and experienced workers, which reveals from adjustments in announced job-prerequisites and from a marginal increase in offered wages and bonus payments. Such a pattern cannot be observed in other groups and might indicate that medium-sized firms seek to produce previously imported inputs themselves.

5.3.2 Firm ownership

Different ownership structures might result in diverse adjustment strategies to tariffs, as firms rely on different decision-making procedures, resources, and networks. For example, while state-owned firms might be theoretically more protected from bankruptcy, foreign owned firms might be able to rely on an international network that allows them to re-route trade flows and cushion the effect of bilateral trade barriers (Flaaen et al., 2020). Domestic private firms would be most directly exposed to market forces and less resilient to short-term policy shocks. Figure C.5 presents estimates for the number of job-ads, separately for state-owned enterprises, foreign owned firms and private domestic enterprises.[34] Figure C.6 displays corresponding results for average wage offers, while Figures C.7 and C.8 show findings for offered non-wage compensation and job-requirements.

[34]Information on firm ownership is provided by the online job-ad platform. State-owned firms includes public institution, state-owned enterprise and government agencies. Foreign-owned firms are enterprises owned by foreign nationals, and the rest are private firms. In the regression sample state-owned and foreign-owned firms account for 5.80% and 28.6% of the total, respectively.

Concerning responses to US tariff increases first, our estimated average effects appear to be driven mainly (and sometimes exclusively) by the privately-owned domestic enterprises. They indicate highly significant reductions in the number job postings, announced wage offers and educational requirements. Chinese SOEs also report lower numbers of job postings, but deviate in their responses regarding wage offers and requested educational background. The job advertising behavior of foreign owned enterprises appears to be virtually unaffected by the US tariffs, which might suggests that these firms have ways to circumvent tariffs.

Turning to China's retaliatory tariffs, besides posting fewer vacancies, privately-owned domestic firms appear to be relatively non-responsive, while China's SOEs show some (but generally imprecisely estimated) adjustments in hiring activity, average compensation offers and job requirements. Foreign-owned firms stand out by significantly lowering their number of job vacancy postings, while increasing wage and bonus payment offers. While strong conclusions from these patterns should be treated with caution, fewer and better-paid job offers by foreign-owned firms could suggest that interrupted supply chains resulted in downscaling of their production and a shift towards more strategic and management-oriented activities in the short term. Chinese firms in turn might be more efficient in switching quickly to alternative suppliers so that additional tariffs on US imports result in fewer observable adjustments, although they also show signs of scaling down by posting fewer job ads.

5.3.3 Further dimensions

Next to firm heterogeneity in terms of size and ownership, also the product mix of their imports and exports might determine tariff effects on labor demand. For example, firms that sell mainly homogeneous (i.e. highly standardized) products face stiffer competition and might be hit harder by a tariff than firms that sell differentiated (or even customized) goods. The latter translates into a relatively lower elasticity of substitution and a smaller tariff effect. Conversely, firms that source mainly homogeneous goods might find it easier to substitute suppliers than those who import differentiated products. Our results in Panel A of Table C.13 seem to support this reasoning when we interact tariff effects with the fraction of homogeneous goods in firms' respective trade basket to estimate adjustments in the number of vacancy postings and average wage offers.[35] Other attributes of job vacancies do not reveal any statistically different effects along this dimension.

We also find some differential adjustments for firms trading a relatively narrow range

[35] We use the conventional classification by Rauch (1999) to determine firms' homogeneous product share in exports and imports in the base year 2016.

of products, which might make it harder to switch to alternative revenue sources. As we show in Panel B of Table C.13, when facing additional US tariffs, such firms offer lower wages and more bonus payments, while requiring lower educational background and more working experience than other firms.[36] Narrow-range importers reveal significantly differential adjustments only for the number of vacancy postings, where they indicate increased hiring activity. This could suggest that relatively "specialized" importers seek to switch towards in-house production, although announced job prerequisites and compensation does not indicate significantly different responses.

6 Concluding remarks

In this paper, we present new evidence on the labor market effects of bilateral tariffs which were reciprocally applied in a recent period of increased political tensions between the US and China. We exploit information from a newly complied data set of vacancy postings in China, which enables us to trace the hiring behavior and advertised job characteristics of firms over time. Our findings suggest that the trade war exerted predominantly destructive effects, which we observe in terms of overall hiring activity, but also in the announced wage compensation.

A novel and unique feature of our study is the use of vacancy postings which we extracted from a popular Chinese online job portal, 51job.com. A key advantage of the data, next to its timely availability, is that it provides detailed insights into the demand side of the labor market. Although it does not allow us to observe firms' actual employment, we can observe when and how often firms post a new vacancy and what they are looking for exactly. Such information reveals insights on firms' short-term future-oriented decision making. We further document that our data is highly representative of the general scale of economic activity across Chinese prefectural cities. Nevertheless, the general tendency of online job vacancy data to be skewed towards relatively higher-paid white-collar jobs implies that also our findings capture only a part of the labor-demand response to the trade war. Blue-collar jobs might reveal similar or perhaps even stronger responses which we do not capture in our paper.

For our analysis, we exploit information from a subset of internationally trading firms, which we identify via matching information reported in China Customs Statistics. Our measure of tariff exposure is therefore constrained to the directly exposed firms, although we could expect that major adjustments to the trade policy shock might propagate via

[36] We define those firms based on the number of goods they exported and imported in 2016 and consider the bottom third as "small-scope" enterprises, using a binary indicator variable as an interaction term.

firms' local supply networks. The sectoral affiliation of firms reported in the online vacancy data prevents us from tracing such networks. Identifying such firm-to-firm trade linkages within China would likely increase the overall scope of exposure to the trade war and allow us to measure and evaluate it more precisely and in a larger sample. We therefore interpret our findings as a lower bound whenever we report aggregates, such as the estimated total reduction in the number of job ads.

Similarly, our study relies on a fairly short period of observations, which extends from May through November 2019, and captures only the most recent round of tariff increases between the US and China. While we are confident that our results are not driven by potentially differential pre-trends across firms, we cannot fully rule out the possibility that major adjustments had already taken place during previous tariff rounds in 2018 (or after the definite announcement of the most recent round). To this end, our estimates might understate the true tariff effects on labor demand. Related to this is also our inability to include more recent data into our sample, given the announcement of the "Phase-one deal" between the two countries in December 2019 and the major economic disruptions that followed the outbreak the Covid-19 pandemic in 2020. A medium-term perspective would have been of particular interest to understand whether firms revoke short-term decisions or whether they delay certain adjustments.

Notwithstanding these limitations, our study contributes to improving our understanding of how firms and labor markets respond to major trade policy shocks and protectionist policies. The results reported for China in this paper appear familiar from related findings for the US, suggesting that similar mechanisms are at work.

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A Data Appendix

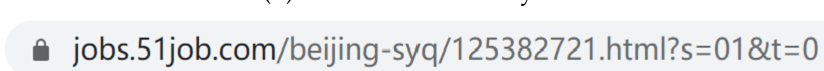
A.1 Web example of a job advertisement

Figure A.1(a) displays a screenshot from the 51job.com website, showing the default format and information of vacancy postings. Panel (b) of the figure displays an example of a corresponding web-address (URL), which is used to uniquely identify a job vacancy.

Figure A.1: Example of an online vacancy posted at 51job.com

(a) Job page

(b) URL-based vacancy ID



Note: Figures depict screenshots from the 51job.com website (red lines and blue text added by authors). Panel (a) shows a typical job ad page from which we extract job information. Panel (b) illustrates how we distinguish vacancies via a unqiue URL. The middle part of the URL denotes the vacancy ID number.

A.2 Data collection method

We collect our data from 51job.com using a web crawler that searches automatically for vacancy postings on this website. To calibrate our search, we take into consideration the structure and refreshing mechanism of the job portal.

At 51job.com, each city has a job-ad capacity limit of 100,000 vacancy postings. That page is refreshed automatically several times per day, so that new job postings (or updated existing postings) appear at the top of the list. Older job ads are passed through to the bottom of the list and can potentially drop out when the limit is reached. We can identify and distinguish vacancies based on their unique ID which is stored in the URL leading to their job page (see Figure A.1(b)). Our final routine is to download the universe of job postings four times per month, at the end of each week, and to remove all duplicates of a job, keeping only their first monthly observation.

Although it is possible that firms update or revise their job ads, we see evidence for this only across months, not within. As shown in Table A.1, most revisions relate to the wage offers, while non-wage benefits and job requirements are less frequently adjusted. Overall, revisions take place only in a small fraction of the observed job postings.

Table A.1: Percentage of job ads with revisions within and across months

	Wage/salary offer	Non-wage benefits	Job requirements	Total revised
Within a month	0.00%	0.00%	0.00%	0.00%
Across months	6.19%	2.12%	1.32%	7.84%

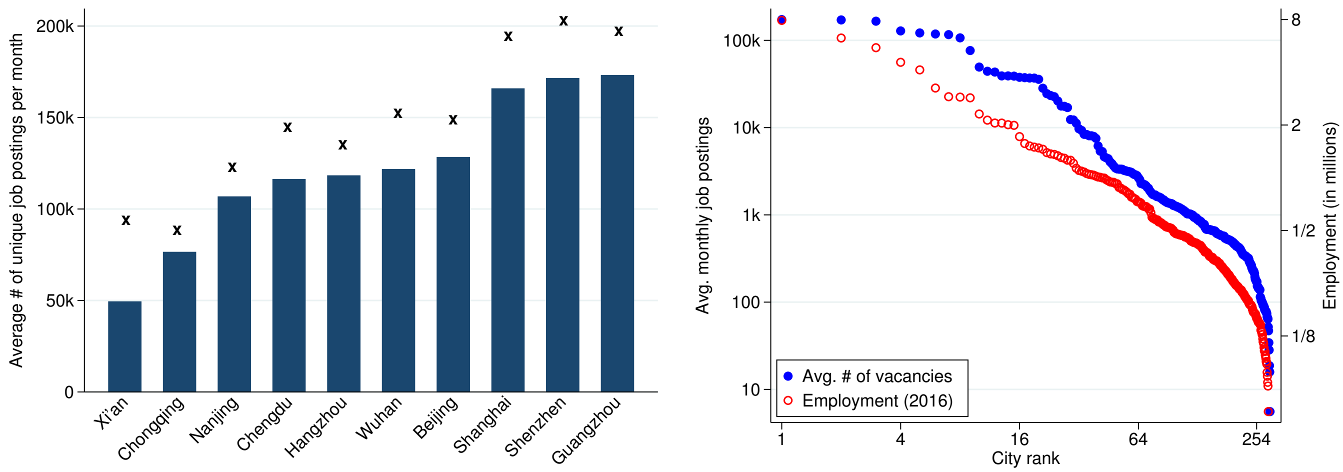
Note: Author's calculations based on data downloaded from 51job.com during the period May-November 2019. Numbers based on a total of 3,897,939 observed job vacancies.

In none of the 297 cities from which we download vacancy postings, the capacity limit of the lists was reached. In fact, only eight cities count more than 100,000 unique job ads in a month and the top three cities report about 175,000 unique job ads on average per month, which is far below the monthly coverage of our download routine (i.e. $4 \times 100{,}000$). Figure A.2(a) depicts the average number of monthly unique job postings in the top 10 cities, as well as their highest value in an individual month of our sample period. In Panel (b) we display the overall distribution of monthly job postings across cities. Its shape is similar to a size-rank distribution of employment across cities, which suggests that the geographic coverage of our sample is fairly representative of China's labor market.[37]

[37] We discuss further aspects regarding the representativeness of our data in Section 2 of the paper.

Figure A.2: Average number of job postings per month across cities

(a) Top 10 Chinese cities (b) Vacancy vs. employment distribution



Note: Authors' calculations based on data downloaded from 51job.com during period May-November 2019. Unique job postings are identified by their URL and counted once per month upon their first appearance. Panel (b) displays the overall distribution of average vacancy postings across cities. It can be compared with the city-size distribution in terms of employment in 2016, as reported in the Chinese Statistical Yearbooks.

Finally, we also inspect the average number of days for which we can observe a job ad in our sample. If a large number of job ads disappears between two download instances in our cycle, we would risk to loose information, due to fast turnover rates. In Table A.2 column (1) we show that essentially all of the job ads we observed for the first time at download time t is still there in $t + 1$ (i.e. about one week later). Columns (2)-(5) suggest that the average and median time span for which a vacancy posting is online corresponds to at least two, but usually more, download cycles. Turnover rates are higher in the top-four cities. This can be inferred also from column (6), where we report the average age of the oldest vacancy posting observed at a particular download instance. It is typically more than eight days in the four mega cities, but ranges between three weeks or even a month on average in the rest of China. The numbers suggest that the chosen parameters for our download routine are generally ahead of the job-ad turnover cycle, so that we obtain a fairly complete record of vacancy postings via 51job.com.

A.3 Descriptive and summary statistics

The descriptive statistics presented in this subsection are discussed in Section 2. Figure A.3 displays trends in the number of monthly unique job vacancies for the manufacturing sector and other industries. Figure A.4 displays standardized log-log relationship be-

Table A.2: Turnover of vacancy postings across cities

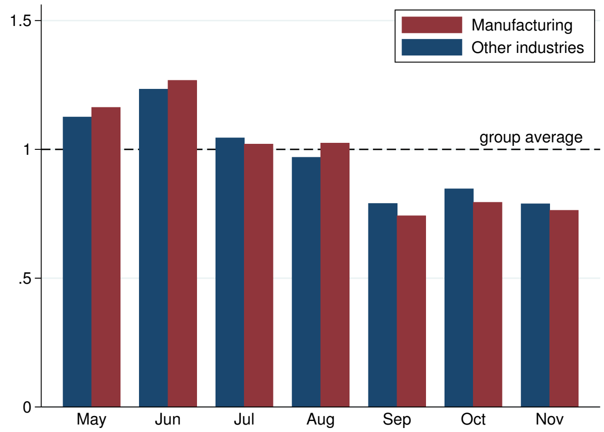
Level of City	(1) % observed in t and $t+1$	(2) # cycles observed: average	(3) # cycles observed: 25th	(4) # cycles observed: median	(5) # cycles observed: 75th	(6) avg. age of oldest ad (days)
Top 4 mega cities	99.51%	2.87 [2.53]	1	2	4	8.27 [6.91]
Provincial capital cities	100%	3.40 [3.92]	2	4	7	19.92 [12.49]
Other prefecture-level city	100%	7.81 [4.60]	4	8	12	30.19 [7.14]

Notes: Four mega cities are Beijing, Shanghai, Guangzhou and Shenzhen. Provincial capital cities refer to 2 central-administrated municipalities (Chongqing and Tianjin), 26 capital cities from 21 provinces and 5 autonomous regions (i.e., 28 in total). The prefecture-level cities reflect the remaining 265 cities. Numbers next to average in brackets denote standard deviations.

tween average number of monthly vacancy postings and city size indicators. Figure A.5 shows the distribution of educational backgrounds in the working population, according to several Censuses since the 2000s, and the corresponding pattern in our job-vacancy data. Comparability of Census and job-vacancy data might be limited by the differential nature of the data, which show realized versus demanded employer-employee relationships respectively. Figure A.6 benchmarks official Census data from China against our vacancy data to inspect their representativeness in terms of industry coverage and concentration.

Table A.3 provides additional details for comparison of our data to the *Zhaopin.com* sample used by Kuhn and Shen (2013) a decade earlier. We note that the wage distribution in our sample differs substantially from theirs, which might be explained partly by higher living standards today compared to ten years ago. Our data are similar to *Zhaopin.com*, however, in terms of skill-requirements, as described in the main text. Likewise, similar patterns can be observed in the fractions of private and state-owned (or state-controlled) enterprises. In terms of industry structure, the expansion of the IT and communications sector is remarkable, while construction and transportation are less represented in our data.

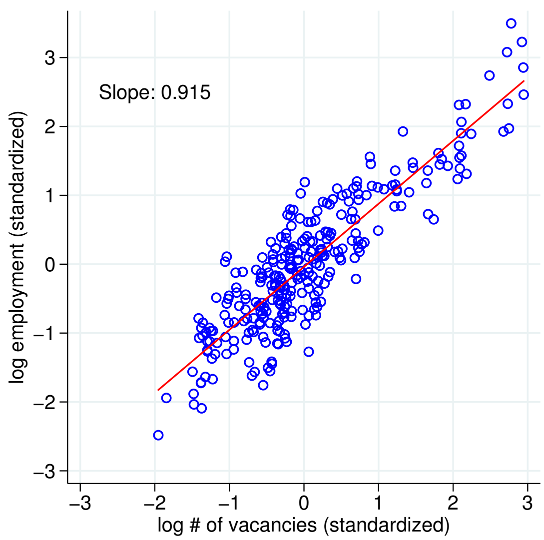
Figure A.3: Trends in number of vacancy postings 2019, manufacturing vs. non-manufacturing



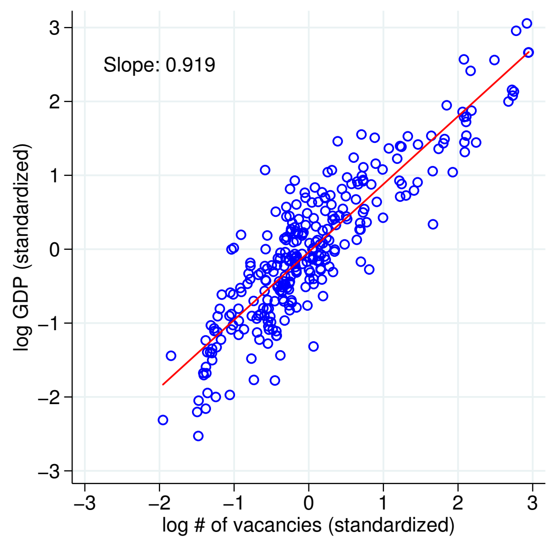
Note: Authors' calculations using data collected from 51job.com during period May-November 2019. For comparability, the vertical axis denotes absolute number of vacancy postings divided by period average.

Figure A.4: Average number of monthly online vacancies versus city size

(a) Employment

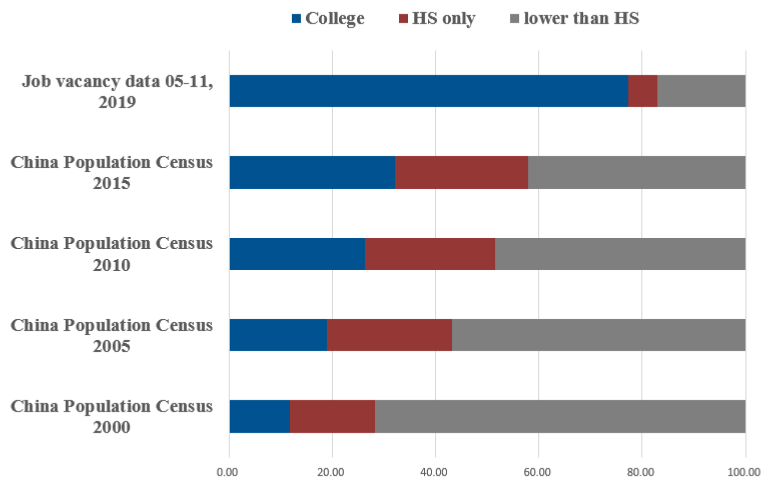


(b) GDP



Note: Authors' calculations using data collected from 51job.com during period May-November 2019 and 2016-information from China Statistical Yearbooks. All variables are expressed in logs and were standardized have mean zero and a standard deviation of 1. Slope indicates estimated coefficient of bivariate linear regression.

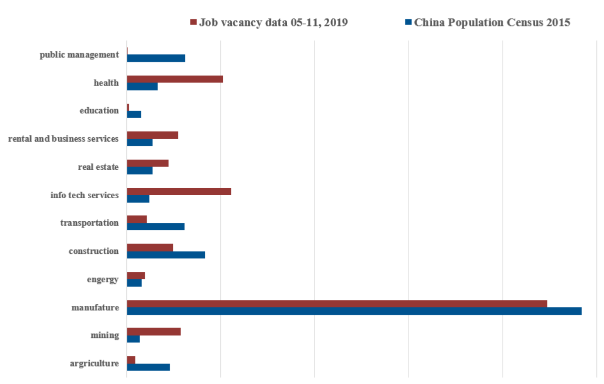
Figure A.5: Distribution of education levels in Census and vacancy data



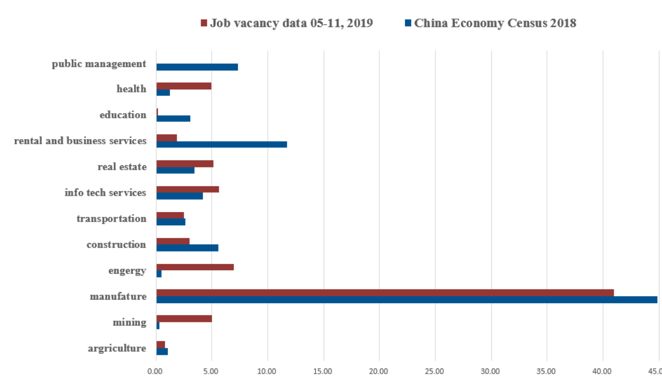
Note: Authors' calculations using data collected from 51job.com (between May and November 2019) and from China's Population Censuses 2000-2015. Proportions in Census data are based on urban employed population. Proportions in job vacancy data reflect requested minimum level of educational background.

Figure A.6: Distribution of employment (vacancies) across industries

(a) Employment



(b) Firms



Note: Panel (a) benchmarks the 2019 industry distribution of job-ads from 51job.com against the industry distribution of employment, according to the 2015 China Population Census. Panel (b) benchmarks the 2019 industry distribution of firms posting ads via 51job.com against the industry distribution of firms, according to the 2018 China Economic Census.

Table A.3: Cross-validation: sample means across data sources

	Sample mean		
	51job (2019)	Zhaopin (2008-10)	Census (2005)
Wage distribution			
1500 or lower (RMB/month)	0.000	0.145	0.778
1501-3000	0.027	0.164	0.176
3001-4000	0.105	0.214	0.021
4001-8000	0.485	0.244	0.022
8001 or higher	0.364	0.126	0.003
Education			
High school or below	0.318	0.114	0.766
Some College	0.682	0.886	0.235
Firm ownership			
Private sector	0.795	0.930	0.589
SOE and collectives	0.052	0.070	0.271
Industry			
Primary, manufacturing and utility	0.432	0.267	0.453
Construction and transportation	0.068	0.135	0.118
IT and communication	0.299	0.185	0.016
Finance, insurance and real estate	0.013	0.052	0.063
Health, education and welfare	0.163	0.033	0.102
Trade, hospitality and entertainment	0.130	0.175	0.165
Public sector	0.034	0.000	0.060

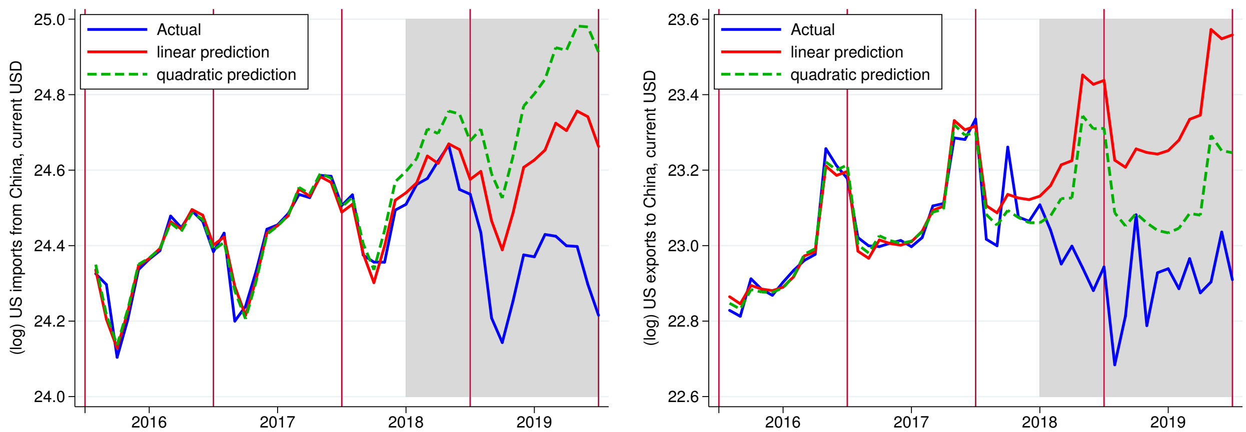
Notes: The first column shows sample moments of our job vacancies sample based on 7 million unique job IDs collected from 51job.com from May to November 2019. The second column is based on the summary statistics from Kuhn and Shen (2013), who collected job ads posted on Zhaopin.com for several periods during 2008 to 2010. The last column is calculated as a comparable sample by Kuhn and Shen (2013). They pick eight highest-income provinces and get the statistics of urban employment from 2005 1% National Population Sample Survey.

B Additional descriptive and summary statistics

B.1 Figures

Figure B.1: Monthly US merchandise trade with China, 2016-2019

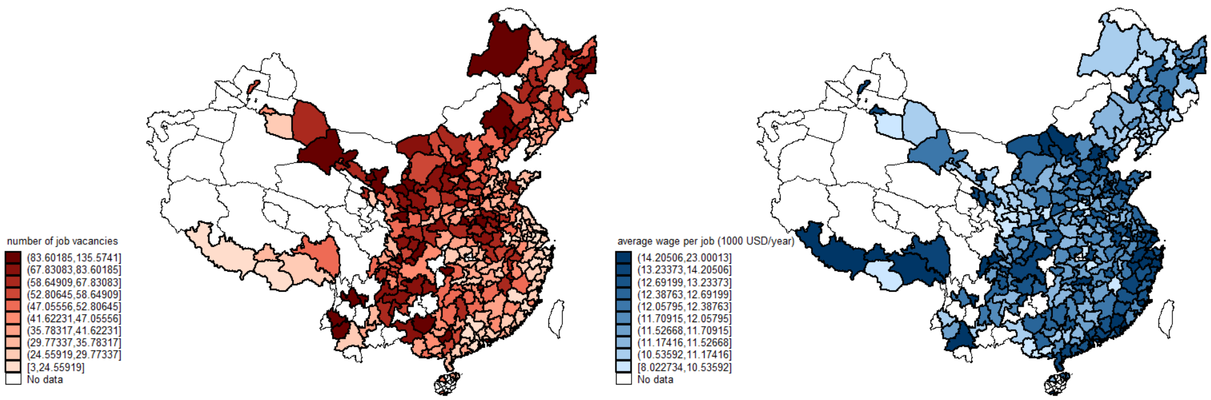
(a) Imports from China (b) Exports to China



Note: Authors' calculations using data from USITC Dataweb. Shaded area indicates period when additional discriminatory tariffs for China came into effect (i.e. since June 2018). Predictions based linear (or quadratic) regression of monthly trade flows during years 2016 and 2017 to capture short-term pre-trade war trends in the data. Vertical lines denote end of the year (i.e. December).

Figure B.2: Number of sampled job vacancies and average wage offers across China

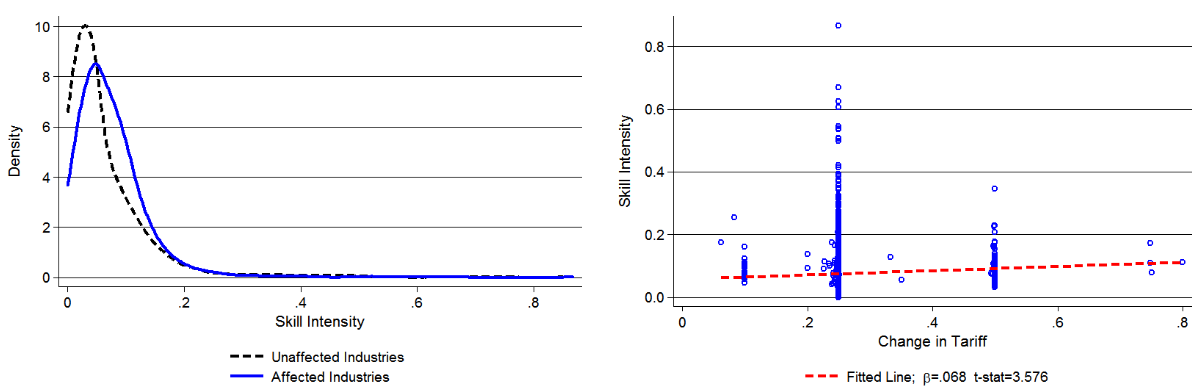
(a) Number of Job Vacancies (b) Annual Average Wage



Note: Authors' calculations based on subsample of data downloaded from 51jobs.com which was matched with firms reporting trade to China Customs for the year 2016. Panel (a) displays the total number of unique job vacancies observed for those firms, across locations. Panel (b) displays the average wage offered in job these vacancies across locations during the period May-November 2019.

Figure B.3: Skill Intensity: Industries Affected by US Tariffs on Chinese Products

(a) Distribution of Industry Skill Intensity (b) Industry Skill Intensity and Tariff Change

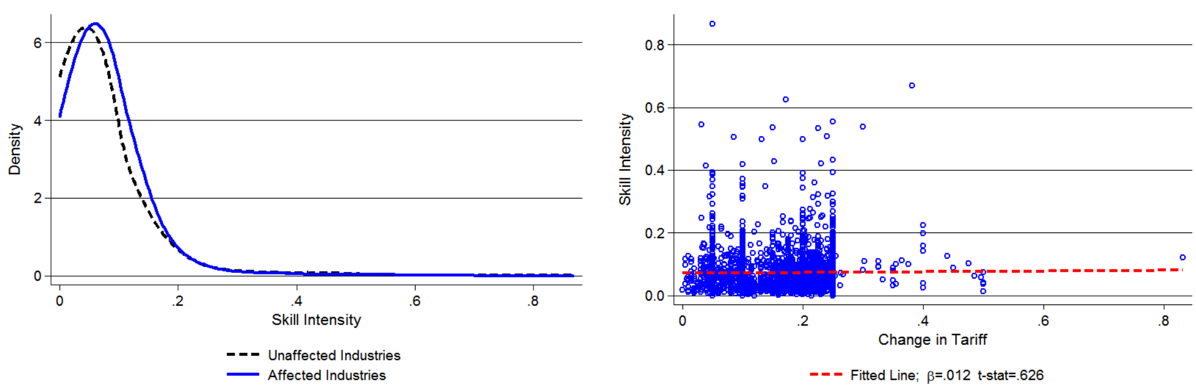


Note: Authors' calculations based on tariff data from Fajgelbaum et al. (2020), Li (2018), and own updates. Skill-intensity is measured as the industry-employment share of skilled workers in 2004, as documented in the Annual Survey of Industry Production (ASIP).

Figure B.4: Skill Intensity: Industries Affected by Chinese Tariffs on US Products

(a) Distribution of Industry Skill Intensity

(b) Industry Skill Intensity and Tariff Change



Note: Authors' calculations based on tariff data from Fajgelbaum et al. (2020), Li (2018), and own updates. Skill-intensity is measured as the industry-employment share of skilled workers in 2004, as documented in the Annual Survey of Industry Production (ASIP).

B.2 Tables

Table B.1: Ten most hiring-intensive industries in matched customs data

Rank	Industry name	% of vacancies	% of firms
1	Electronic technology / Semiconductor / Integrated circuit	11.52	10.27
2	Machinery / Equipment / Heavy industry	11.02	13.82
3	Pharmaceutical / Bioengineering	7.71	3.68
4	Automobile and Accessories	6.84	7.19
5	Trading / Import & Export	6.54	14.40
6	Fast moving consumer goods (food, beverages, cosmetics)	6.38	3.92
7	Medical equipment	4.95	3.75
8	Instrumentation / Industrial Automation	3.76	4.09
9	Apparel / Textile / Leather	3.67	4.55
10	Furniture / Home Appliances / Toys / Gifts	3.31	2.60
	Cumulative (sum)	65.69	68.27

Note: Authors' calculations based on data downloaded from 51job.com during the period May-November 2019 and matched firms reported in 2016 China Customs statistics. Industry names translated from description on 51job.com. Percentages represent industries' share in total number of unique job-postings and firms observed throughout the sample period.

Table B.2: Hiring activity and job attributes by month, averages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Month (2019)	May	Jun	Jul	Aug	Sep	Oct	Nov
Wage offer (10,000 RMB/year)							
Average	9.58	9.74	10.14	9.88	10.71	10.53	10.41
Minimum	7.55	7.69	8.00	7.78	8.43	8.30	8.22
Maximum	11.60	11.79	12.29	11.98	12.99	12.75	12.60
Non-wage compensation (share of vacancies)							
Subsidies	0.57	0.58	0.58	0.57	0.55	0.55	0.56
Bonus	0.50	0.51	0.50	0.50	0.49	0.48	0.49
Insurance package	0.72	0.73	0.73	0.72	0.72	0.71	0.71
Job requirements							
Average work experience (years)	1.71	1.74	1.80	1.74	1.79	1.76	1.74
Minimum	1.53	1.56	1.61	1.56	1.59	1.57	1.56
Maximum	1.88	1.93	2.00	1.92	1.98	1.94	1.93
College or higher (fraction)	0.77	0.77	0.77	0.77	0.79	0.78	0.78
Number of firms	20,458	20,924	19,065	19,773	15,301	16,084	15,534
Number of unique jobs	232,000	258,058	199,334	197,929	146,535	153,711	141,982

Notes: Author's calculations based on data collected from 51job.com and matched firms from China Custom statistics. Monthly summary statistics reflect subsamples of aggregate summary statistics presented in main text of the paper, featuring 30,123 firms and 607,532 unique job postings in the period May-November 2019.

Table B.3: Average product and firm-level exposure to tariffs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Product-level exposure				Firm-level exposure			
	$\bar{\tau}_t^{\text{US}}$		$\bar{\tau}_t^{\text{CHN}}$		$\text{Tariff}_{ft}^{\text{US}}$		$\text{Tariff}_{ft}^{\text{CHN}}$	
Time (month-year)	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Jan 2018	0.036	0.102	0.092	0.069	0.029	0.038	0.058	0.043
Feb 2018	0.036	0.103	0.092	0.069	0.031	0.042	0.058	0.043
Mar 2018	0.036	0.103	0.092	0.069	0.031	0.042	0.058	0.043
Apr 2018	0.045	0.110	0.095	0.075	0.032	0.044	0.060	0.047
May 2018	0.045	0.110	0.095	0.075	0.032	0.044	0.059	0.047
Jun 2018	0.045	0.110	0.095	0.075	0.032	0.044	0.059	0.047
Jul 2018	0.074	0.129	0.095	0.100	0.095	0.099	0.059	0.060
Aug 2018	0.074	0.129	0.095	0.100	0.095	0.099	0.059	0.060
Sep 2018	0.084	0.139	0.104	0.110	0.117	0.125	0.078	0.085
Oct 2018	0.144	0.130	0.172	0.100	0.169	0.120	0.141	0.083
Nov 2018	0.144	0.130	0.167	0.098	0.169	0.120	0.138	0.081
Dec 2018	0.144	0.130	0.167	0.098	0.169	0.120	0.138	0.081
Jan 2019	0.144	0.130	0.166	0.097	0.169	0.120	0.136	0.078
Feb 2019	0.144	0.130	0.166	0.097	0.169	0.120	0.136	0.078
Mar 2019	0.144	0.130	0.166	0.097	0.169	0.120	0.136	0.078
Apr 2019	0.144	0.130	0.166	0.097	0.169	0.120	0.136	0.078
May 2019	0.232	0.151	0.166	0.097	0.247	0.141	0.136	0.078
Jun 2019	0.232	0.151	0.251	0.114	0.247	0.141	0.206	0.096
Jul 2019	0.232	0.151	0.251	0.114	0.247	0.141	0.206	0.096
Aug 2019	0.232	0.151	0.251	0.114	0.247	0.141	0.206	0.096
Sep 2019	0.232	0.151	0.251	0.114	0.247	0.141	0.206	0.096
Oct 2019	0.232	0.151	0.251	0.114	0.247	0.141	0.206	0.096
Nov 2019	0.232	0.151	0.251	0.114	0.247	0.141	0.206	0.096
Dec 2019	0.232	0.151	0.251	0.114	0.247	0.141	0.206	0.096

Notes: Authors' calculations based on China Customs data from 2016 and tariff information from various sources, as described in the main text. Columns (1)-(4) display average product level exposure (and standard deviations) to US tariffs and Chinese retaliation, observed at the 6-digit Harmonized Schedule (HS6) level. Columns (5)-(8) display corresponding measure of firm-level exposure, as described in Section 4 of the paper.

Table B.4: Variable Description

Variable	Description
Wage	A numeric variable that captures the wage level (in 1000 US dollars) for each job vacancy. In each job ad, the wage information is listed in the format as a closed interval. We record two end points as the minimum wage and maximum wage, respectively, and take the midpoint of the interval as the mean wage.
Bonus	An indicator variable that equals if employers commit to provide a performance appraisal in addition to basic wage for a job.
Subsidy	An indicator variable that equals to one if employers commit to provide overtime subsidies, transportation, communication, and meal allowance for a job.
Insurance	An indicator variable that equals to one if employers commit to provide five insurances (unemployment, endowment, medial, work-related injury and maternity) for a job.
College Degree Requirement	An indicator variable that equals to one for jobs that require at least a college degree. Employers choose from the following standardized options the minimum level of education required for each job vacancy: middle school, high school, (3 or 4 years) college degree, master degree, and PhD degree.
Experience Requirement	A numeric variable that captures the years of working experience required for each job vacancy. Employers choose from the following standardized options the years of working experience required for each job vacancy: no experience needed, 1 year, 2 years, 3-4 years, 5-7 years, 8-9 years, and 10 years or above. For each interval, we record two end points and the midpoint as the minimum experience, maximum experience and mean experience, respectively. We record zero for the option "no experience needed", and 10 the option "10 years or above".

Table B.5: Descriptive Statistics by firms with varying length of Job Posting

Sub-sample of firms	Dep. variables		Firm ownership		Firm size	
	# of vacancies	avg. wage offer	State owned	Foreign owned	Very large >5,000	Very small <50
1-month firms: 7,337						
Mean	4.01	8.38	0.06	0.28	0.01	0.34
Std.Dev.	6.41	5.71				
2-month firms: 5,597						
Mean	4.10	8.52	0.05	0.32	0.01	0.27
Std.Dev.	7.25	5.58				
3-month firms: 4,969						
Mean	4.59	8.76	0.05	0.30	0.01	0.18
Std.Dev.	13.83	10.95				
4-month firms: 4,110						
Mean	4.56	8.92	0.06	0.30	0.02	0.11
Std.Dev.	8.20	9.04				
5-month firms: 3,299						
Mean	5.10	9.56	0.05	0.27	0.02	0.07
Std.Dev.	9.49	11.11				
6-month firms: 2,536						
Mean	6.09	9.78	0.05	0.26	0.02	0.04
Std.Dev.	11.10	6.65				
7-month firms: 2,275						
Mean	13.31	10.79	0.06	0.22	0.06	0.01
Std.Dev.	36.39	8.97				

Notes: Author's calculations based on data collected from 51job.com. Summary statistics for sample of 30,123 firms matched with China Customs information, May-November 2019. Vacancies are uniquely identified across months.

Table B.6: Distribution of sampled Firms across Industries on 51job.com

Industry Classification	Number of Firms (%)
Trading / Import & Export	14.40%
Machinery / Equipment / Heavy industry	13.82%
Electronic technology / Semiconductor / Integrated circuit	10.27%
Automobile and Accessories	7.19%
Apparel / Textile / Leather	4.55%
Instrumentation / Industrial Automation	4.09%
Fast moving consumer goods (food, beverages, cosmetics)	3.92%
Raw materials and processing	3.88%
Medical equipment	3.75%
Pharmaceutical / Bioengineering	3.68%
Petroleum / Chemical / Mineral / Geology	3.66%
Furniture / Home Appliances / Toys / Gifts	2.60%
Construction / Building Materials / Engineering	2.28%
Communication / Telecom / Network equipment	1.92%
Computer software	1.92%
Transportation and Logistics	1.92%
Wholesale and retail	1.73%
Printing / Packaging / Paper	1.66%
E-Commerce	1.41%
New Energy	1.28%
Environmental protection	1.19%
Diversified business group company	1.03%
Electrical / Electricity / Water conservancy	0.76%
Agriculture, forestry, animal husbandry and fisheries	0.63%
Computer service (system, data service, maintenance)	0.61%
Medical / Nursing / Hygiene	0.56%
Office supplies and equipment	0.48%
Computer hardware	0.45%
Aerospace	0.44%
Home / Interior Design / Décor	0.43%
Testing and certification	0.37%
Finance / Investment / Securities	0.36%
Luxury / Collectibles / Crafts / Jewelry	0.34%
Entertainment / Leisure / Sports	0.27%
Hotel / Tourism	0.24%
Real estate	0.23%
Unclassified	0.21%
Professional services (consulting, human resources, accounting)	0.20%
Health & Beauty	0.16%
Academic research	0.14%
Education / Training / Institutions	0.14%
Extractive industry / Smelting	0.14%
Film / Media / Art / Culture Communication	0.11%
Catering	0.10%
Public Relation / Marketing / Exhibition	0.10%
Banking	0.07%
Property Management	0.07%
Advertising Services	0.06%
Government / Public utility	0.03%
Rental service	0.03%
Outsourcing Service	0.03%
Media / Publishing	0.02%
Online game	0.02%
Insurance	0.02%
Daily life service	0.01%
Legal service	0.01%
Intermediary service	0.01%
Non-profit organizations	0.01%

Notes: Table shows names of all 60 industry affiliations reported on the online job platform *Qian Cheng Wu You 51job.com*. Next to industry names, we display the percentage of firms in our final sample that belong to that industry.

C Additional results and robustness checks

Table C.1: Offered wages, tariff exposure and educational background requirements

Dependent variable: average wage offer	(1)	(2)
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	0.014	0.006
	(0.046)	(0.045)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	-0.071*	-0.059
	(0.039)	(0.035)
$Share^{College}_{ft}$		0.255***
		(0.012)
Observations	107,448	107,448
R-squared	0.738	0.751
Firm FE	Y	Y
City-Month FE	Y	Y
Sector-Month FE	Y	Y

Notes: Regression results based on job vacancy data observed between May and November 2019. Dependent variable measures log average wage/salary offers advertised in firms' vacancy postings. Column (1) reproduces our main finding from column (6) in Table 3. Column (2) adds required college education as an additional control variable. Standard errors adjusted for clustering at city-month level are displayed in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table C.2: Number of vacancy postings and fictional tariff exposure, placebo estimation

Dependent variable:	(1)	(2)	(3)	(4)
	Stock (all job vacancies)		Flow (new job vacancies)	
Number of vacancies (N^v_{ft})	OLS	Poisson	OLS	Poisson
$\ln(1+\widetilde{\text{Tariff}}^{\text{CHN}}_{ft-1})$	-3.267	-0.219	-3.445	-0.162
	(2.079)	(0.203)	(2.220)	(0.270)
$\ln(1+\widetilde{\text{Tariff}}^{\text{US}}_{ft-1})$	-1.801	-0.104	-3.993	-0.133
	(1.724)	(0.178)	(2.624)	(0.309)
Number of Boostraps	30	30	30	30
Firm FE	Y	Y	Y	Y
City-Month FE	Y	Y	Y	Y
Sector-Month FE	Y	Y	Y	Y

Notes: Table shows results of placebo regressions of vacancy postings, based on fictional tariff exposure and a bootstrapped sample (see Section 5.2.1). Standard errors in parentheses are clustered a the city and month level. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table C.3: Wage offers and fictional tariff exposure, placebo estimation

Dependent variable: Wage/salary ($\ln w_{ft}$)	(1) Minimum	(2) Maximum	(3) Average	(4) Dispersion
$\ln(1+\widetilde{\text{Tariff}}^{\text{CHN}}_{ft-1})$	0.009	0.020	0.017	0.011
	(0.040)	(0.042)	(0.041)	(0.018)
$\ln(1+\widetilde{\text{Tariff}}^{\text{US}}_{ft-1})$	-0.017	-0.018	-0.017	-0.001
	(0.033)	(0.031)	(0.031)	(0.015)
Number of Boostraps	30	30	30	30
Firm FE	Y	Y	Y	Y
City-Month FE	Y	Y	Y	Y
Sector-Month FE	Y	Y	Y	Y

Notes: Table shows results of placebo regressions of advertised wage offers, based on fictional tariff exposure and a bootstrapped sample (see Section 5.2.1). Standard errors in parentheses are clustered a the city and month level. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table C.4: Non-wage compensation and fictional tariff exposure, placebo estimation

Dependent variable: Share of vacancies offering	(1) Bonuses	(2) Subsidies	(3) Insurances
$\ln(1+\widetilde{\text{Tariff}}^{\text{CHN}}_{ft-1})$	0.021	0.005	0.006
	(0.039)	(0.029)	(0.028)
$\ln(1+\widetilde{\text{Tariff}}^{\text{US}}_{ft-1})$	-0.005	-0.014	-0.004
	(0.028)	(0.035)	(0.029)
Number of Boostrap	30	30	30
Firm FE	Y	Y	Y
City-Month FE	Y	Y	Y
Sector-Month FE	Y	Y	Y

Notes: Table shows results of placebo regressions of advertised non-wage compensation, based on fictional tariff exposure and a bootstrapped sample (see Section 5.2.1). Standard errors in parentheses are clustered a the city and month level. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table C.5: Job requirements and fictional tariff exposure, placebo estimation

Dependent variable:	(1) College	(2) Previous work experience (years)	(3)	(4)
	Fraction	Minimum	Average	Maximum
$\ln(1+\widetilde{\text{Tariff}}^{CHN}_{ft-1})$	0.011	0.029	0.017	0.006
	(0.040)	(0.041)	(0.167)	(0.193)
$\ln(1+\widetilde{\text{Tariff}}^{US}_{ft-1})$	0.007	0.004	-0.005	-0.013
	(0.034)	(0.138)	(0.161)	(0.184)
Number of Boostrap	30	30	30	30
Firm FE	Y	Y	Y	Y
City-Month FE	Y	Y	Y	Y
Sector-Month FE	Y	Y	Y	Y

Notes: Table shows results of placebo regressions of advertised job requirements, based on fictional tariff exposure and a bootstrapped sample (see Section 5.2.1). Standard errors in parentheses are clustered a the city and month level. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table C.6: Historical employment and wage growth in exposed firms, pre-trends

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Employment growth				Avg. wage growth			
$\Delta\text{Tariff}^{US}_{f,2018-2019}$	0.115*	0.043	0.061	0.071	-0.180***	-0.098	-0.086	-0.094
	(0.062)	(0.082)	(0.082)	(0.078)	(0.067)	(0.091)	(0.094)	(0.093)
$\Delta\text{Tariff}^{CHN}_{f,2018-2019}$	-0.072	-0.046	-0.034	-0.053	0.084	0.059	0.051	0.066
	(0.076)	(0.089)	(0.093)	(0.097)	(0.109)	(0.111)	(0.119)	(0.118)
Observations	4,785	4,725	4,669	4,669	4,785	4,725	4,669	4,669
R-squared	0.001	0.076	0.129	0.147	0.002	0.072	0.123	0.131
Firm Control				Y				Y
City FE			Y	Y			Y	Y
Industry FE		Y	Y	Y		Y	Y	Y

Note: Table shows cross-sectional firm-level regression results of employment and wage growth between 2012 and 2013. Growth measured as log-differences in employment and wage compensation per employee, as reported for corresponding years in the ASIP. Standard errors in parentheses are adjusted for clustering at the city level. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table C.7: Number of vacancies postings and tariff exposure, timing of effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Stock (all job vacancies)			Flow (new job vacancies)		
Number of vacancies (N^v_{ft})	OLS	OLS	Poisson	OLS	OLS	Poisson
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	-2.577	-2.317	0.097	-6.485**	-6.307**	0.329
	(2.516)	(2.484)	(0.268)	(2.343)	(2.408)	(0.418)
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-3})$	-0.079	-0.349	0.547**	-1.627***	-1.597***	0.003
	(1.615)	(1.747)	(0.222)	(0.398)	(0.271)	(0.127)
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-5})$	-2.381**	-2.223**	-0.475***	-1.401***	-1.219**	-0.963***
	(0.895)	(0.877)	(0.149)	(0.284)	(0.380)	(0.337)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	-2.275*	-1.701**	-0.223**	-2.379*	-5.729***	-0.540*
	(1.092)	(0.670)	(0.104)	(1.042)	(1.308)	(0.284)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-3})$	-0.379	-2.719*	-0.336*	0.608	-0.695	-0.257
	(1.275)	(1.274)	(0.181)	(0.547)	(0.447)	(0.177)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-5})$	-2.467**	-2.165*	-0.299*	-0.645*	-0.227	0.097
	(0.958)	(1.006)	(0.171)	(0.301)	(0.368)	(0.426)
Observations	189,272	188,923	188,730	189,196	188,880	188,479
R-squared	0.763	0.767		0.522	0.537	
City Controls	Y			Y		
Month FE	Y			Y		
Firm FE	Y	Y	Y	Y	Y	Y
City-Month FE		Y	Y		Y	Y
Sector-Month FE		Y	Y		Y	Y

Notes: Table shows fixed effects OLS and Poisson regression results for the number of vacancy postings by firms over time, facing differential degrees of exposure to tariffs. Robust standard errors in parentheses are adjusted for clustering at the city and month level (for FEOLS) and bootstrapped (for Poisson). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table C.8: Number of vacancy postings and exposure to tariffs (three-period lag)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Stock (all job vacancies)			Flow (new job vacancies)		
Number of vacancies (N^v_{ft})	OLS	OLS	Poisson	OLS	OLS	Poisson
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-3})$	-2.256	-2.259	0.432	-5.345**	-5.147**	-0.042
	(2.193)	(2.290)	(0.328)	(2.000)	(1.976)	(0.502)
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-3})$	-2.431	-4.499**	-0.563**	-0.690	-2.909	-0.502*
	(1.422)	(1.564)	(0.227)	(0.792)	(1.779)	(0.302)
Observations	189,272	188,909	188,705	189,196	188,880	188,479
R-squared	0.763	0.767		0.522	0.536	
City Controls	Y			Y		
Month FE	Y			Y		
Firm FE	Y	Y	Y	Y	Y	Y
City-Month FE		Y	Y		Y	Y
Sector-Month FE		Y	Y		Y	Y

Notes: Table shows fixed effects OLS and Poisson regression results for the number of vacancy postings by firms over time, facing differential degrees of exposure to tariffs. Robust standard errors in parentheses are adjusted for clustering at the city and month level (for FEOLS) and bootstrapped (for Poisson). Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table C.9: Wage offers and exposure to tariffs (three-period lag)

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wage/salary $\ln w_{ft}$	Minimum		Maximum		Average		Dispersion	
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-3})$	-0.042	-0.049	-0.050	-0.060*	-0.049	-0.058*	-0.008	-0.011
	(0.032)	(0.036)	(0.029)	(0.028)	(0.028)	(0.029)	(0.022)	(0.023)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-3})$	-0.046	-0.043	-0.047	-0.037	-0.045	-0.038	-0.001	0.006
	(0.050)	(0.056)	(0.041)	(0.049)	(0.044)	(0.051)	(0.012)	(0.011)
Observations	107,800	107,448	107,800	107,448	107,800	107,448	107,800	107,448
R-squared	0.738	0.742	0.732	0.736	0.734	0.738	0.736	0.740
City Controls	Y		Y		Y		Y	
Month FE	Y		Y		Y		Y	
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
City-Month FE		Y		Y		Y		Y
Sector-Month FE		Y		Y		Y		Y

Notes: Table shows fixed effects OLS regression results for offered wages in vacancy postings by firms over time, facing differential degrees of exposure to tariffs. Robust standard errors in parentheses are adjusted for clustering at the city and month level. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table C.10: Non-wage compensation and exposure to tariffs (three-period lag)

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Share of vacancies offering	Bonus		Subsidy		Insurance	
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-3})$	0.002	0.008	0.015	0.024	0.034	0.043
	(0.043)	(0.042)	(0.036)	(0.033)	(0.034)	(0.032)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-3})$	0.020	0.006	0.009	-0.020	0.015	0.002
	(0.029)	(0.027)	(0.020)	(0.013)	(0.025)	(0.029)
Observations	107,800	107,442	107,800	107,442	107,800	107,442
R-squared	0.855	0.857	0.863	0.865	0.864	0.866
City Controls	Y		Y		Y	
Month FE	Y		Y		Y	
Firm FE	Y	Y	Y	Y	Y	Y
City-Month FE		Y		Y		Y
Sector-Month FE		Y		Y		Y

Notes: Table shows fixed effects OLS regression results for prevalence of different forms of non-wage compensation in vacancy postings by firms over time, facing differential degrees of exposure to tariffs. Robust standard errors in parentheses are adjusted for clustering at the city and month level. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table C.11: Job requirements and exposure to tariffs (three-period lag)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Previous work experience (in years)						College degree	
	Minimum		Maximum		Average		Fraction	
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-3})$	0.052	0.110	0.038	0.115	0.045	0.113	-0.005	-0.006
	(0.108)	(0.126)	(0.127)	(0.154)	(0.117)	(0.139)	(0.065)	(0.062)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-3})$	-0.051	0.008	-0.037	0.035	-0.044	0.022	-0.023	0.008
	(0.103)	(0.098)	(0.147)	(0.143)	(0.125)	(0.120)	(0.049)	(0.046)
Observations	107,544	107,181	107,544	107,181	107,544	107,181	107,800	107,437
R-squared	0.745	0.748	0.744	0.748	0.745	0.749	0.712	0.716
City Controls	Y		Y		Y		Y	
Month FE	Y		Y		Y		Y	
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
City-Month FE		Y		Y		Y		Y
Sector-Month FE		Y		Y		Y		Y

Notes: Table shows fixed effects OLS regression results for job requirements specified in vacancy postings by firms over time, facing differential degrees of exposure to tariffs. Robust standard errors in parentheses are adjusted for clustering at the city and month level. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

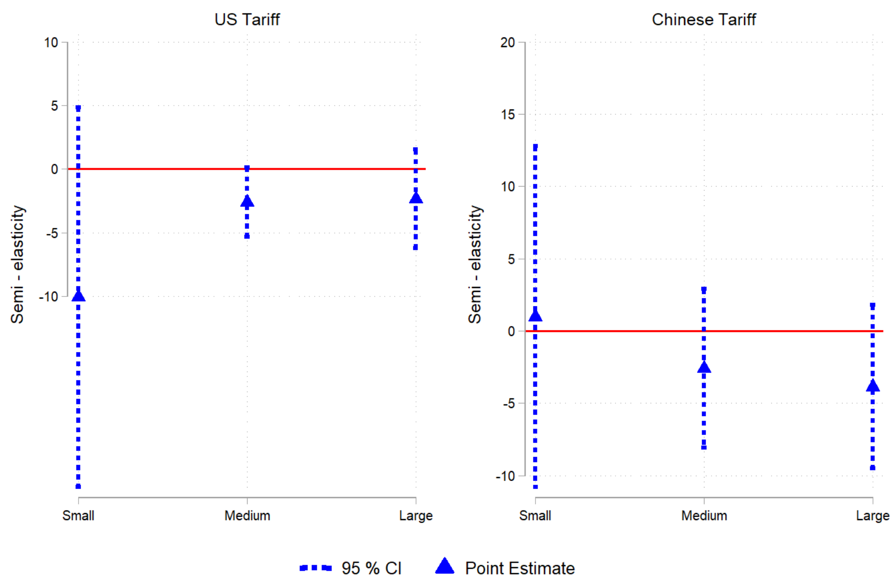
Table C.12: Effect of Tariffs by control groups

Dependent variable: Number of vacancies (N^{v}_{ft})	(1) Stock (all job vacancies) Control Group 1	(2) Stock (all job vacancies) Control Group 2	(3) Flow (new job vacancies) Control Group 1	(4) Flow (new job vacancies) Control Group 2
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	-2.555	-0.073	-6.998**	-4.646**
	(3.060)	(2.879)	(2.282)	(1.660)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	-4.367**	-2.925*	-6.501***	-3.420*
	(1.588)	(1.473)	(1.389)	(1.591)
Observations	148,806	113,918	148,760	113,852
R-squared	0.735	0.727	0.448	0.451
Firm FE	Y	Y	Y	Y
City-Month	Y	Y	Y	Y
Ind-Month	Y	Y	Y	Y

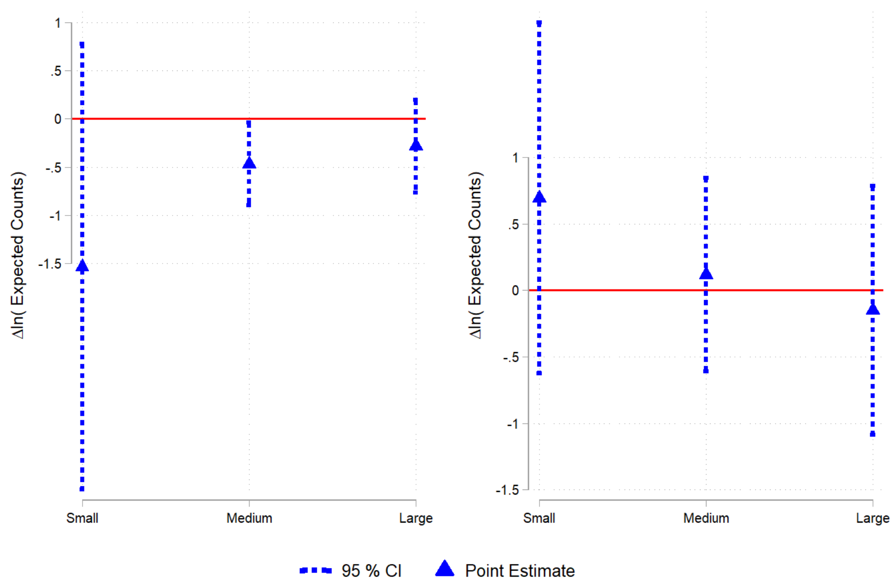
Notes: Table shows fixed effects OLS regression results for the number of job vacancies posted by firms over time, facing differential degrees of exposure to tariffs. Control group 1 reflects sample consisting of firms directly affected by tariffs during 2019-round of trade war and unaffected firms that did not trade with the US in base year 2016. Control group 2 reflects sample consisting of firms directly affected by tariffs during 2019-round of trade war and firms traded with the US in base year 2016 but were unaffected. Standard errors in parentheses are adjusted for clustering at city and month level. Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure C.1: Number of vacancy postings and tariff exposure by size of firms

(a) semi-elasticity

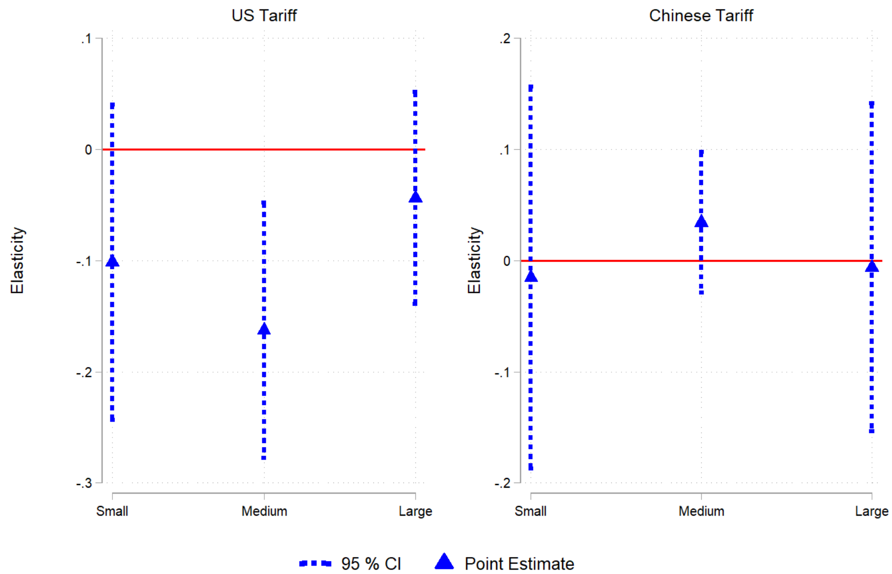


(b) Δln(Expected Counts)



Notes: Figures show coefficient estimates and 95% confidence intervals for regressions using different subsamples of firms, as indicated on the horizontal axis. Left panels indicate estimated effects of additional US tariffs on respective outcome variables denoted in the title of the figure. Right panels indicate respectively estimated effects of China's retaliation tariffs in the trade war.

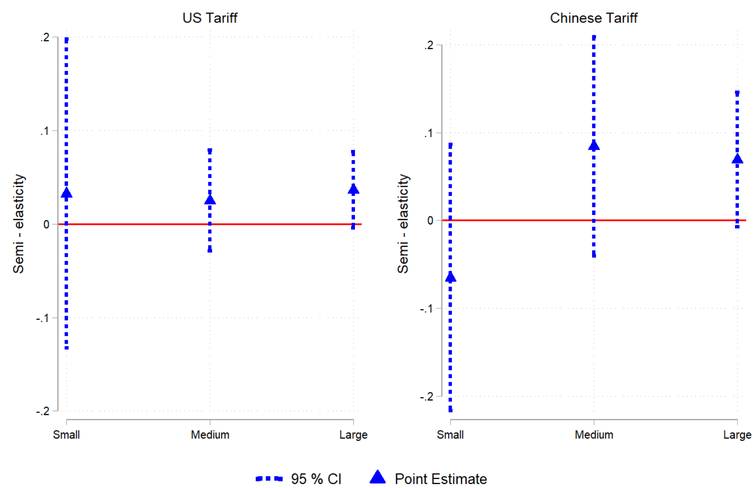
Figure C.2: Average offered wages and tariff exposure by size of firms



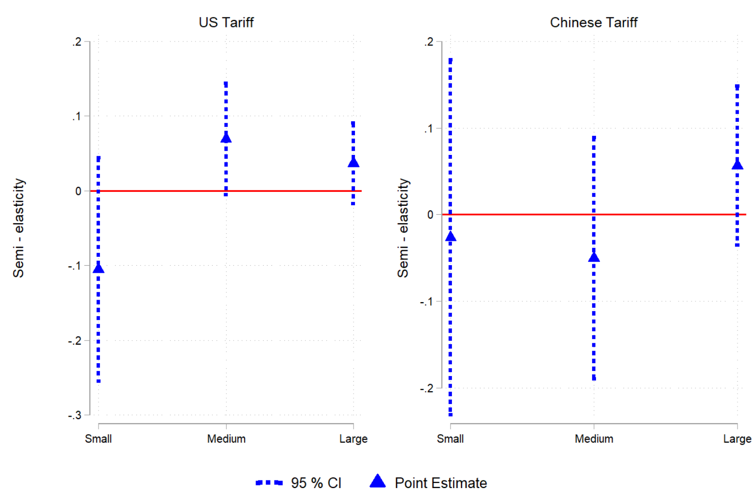
Notes: Figures show coefficient estimates and 95% confidence intervals for regressions using different subsamples of firms, as indicated on the horizontal axis. Left panels indicate estimated effects of additional US tariffs on respective outcome variables denoted in the title of the figure. Right panels indicate respectively estimated effects of China's retaliation tariffs in the trade war.

Figure C.3: Offered non-wage compensation and tariff exposure by size of firms

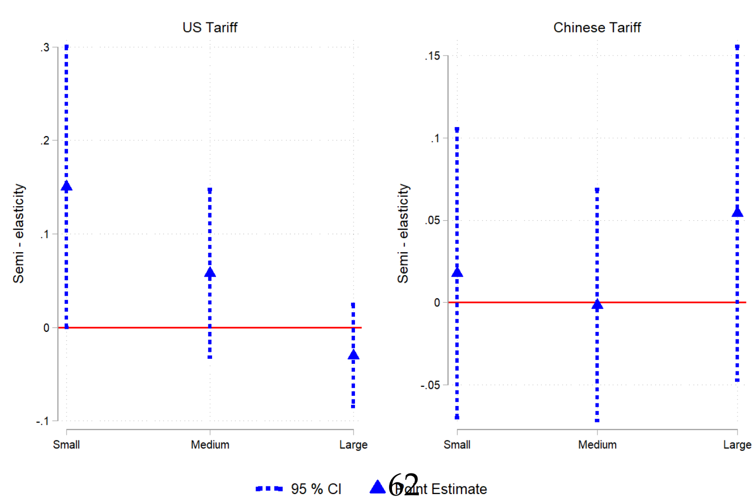
(a) Share of Jobs Offering Bonus



(b) Share of Jobs Offering Subsidy



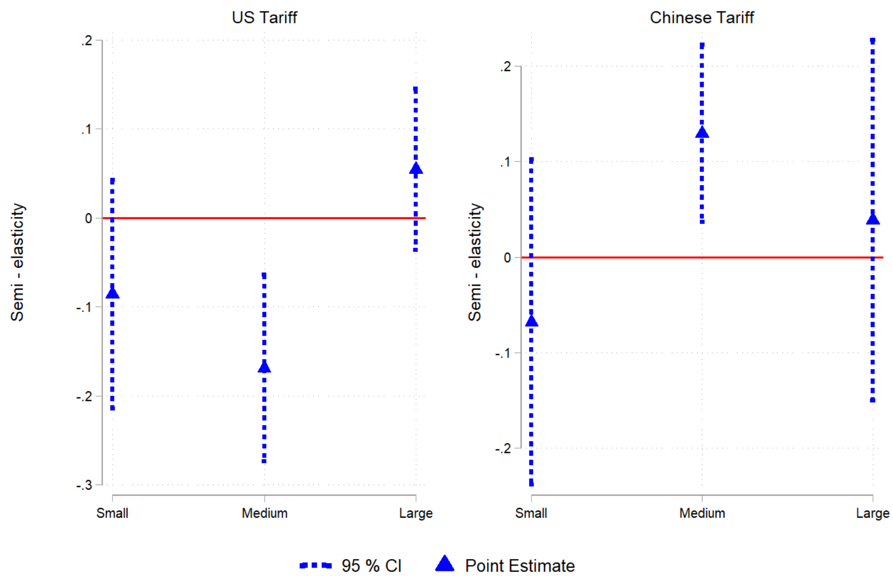
(c) Share of Jobs Offering Insurance



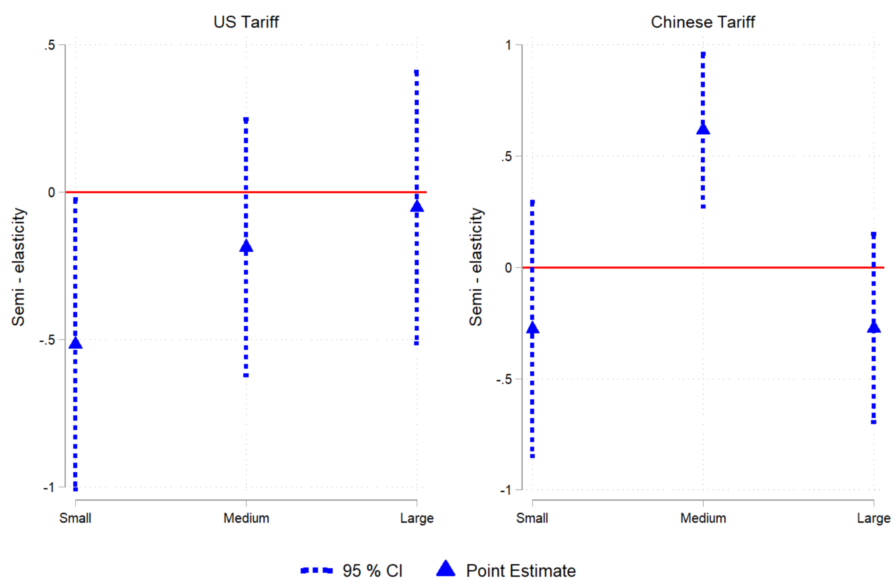
Notes: Figures show coefficient estimates and 95% confidence intervals for regressions using different sub-

Figure C.4: Job requirements and tariff exposure by size of firms

(a) College Degree (or above)

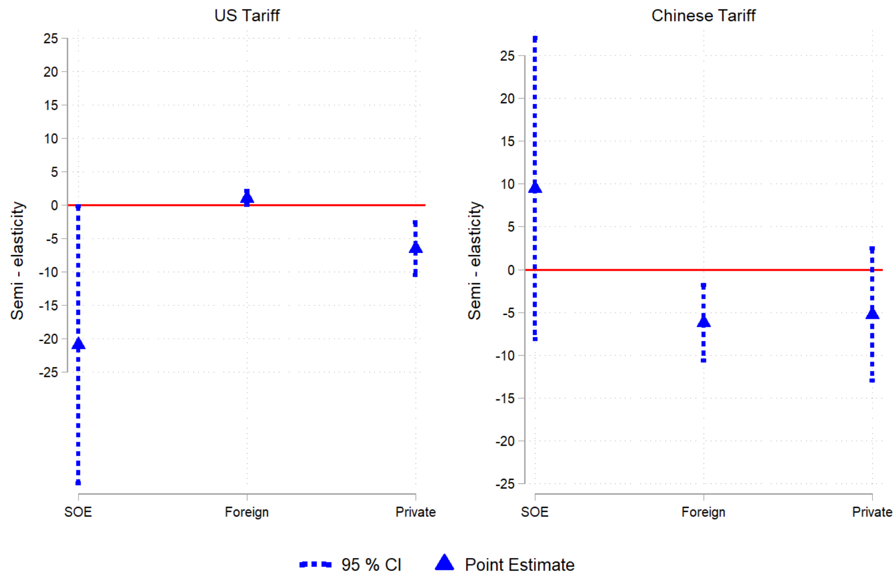


(b) Work experience (years)



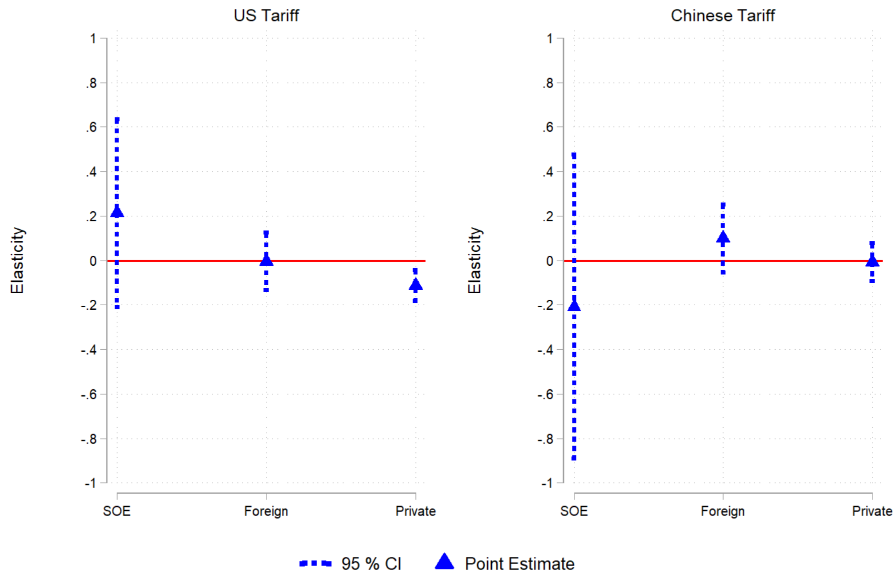
Notes: Figures show coefficient estimates and 95% confidence intervals for regressions using different sub-samples of firms, as indicated on the horizontal axis. Left panels indicate estimated effects of additional US tariffs on respective outcome variables denoted in the title of the figure. Right panels indicate respectively estimated effects of China's retaliation tariffs in the trade war.

Figure C.5: Number of vacancy postings and tariff exposure by firm ownership



Notes: Figures show coefficient estimates and 95% confidence intervals for regressions using different subsamples of firms, as indicated on the horizontal axis. Left panels indicate estimated effects of additional US tariffs on respective outcome variables denoted in the title of the figure. Right panels indicate respectively estimated effects of China's retaliation tariffs in the trade war.

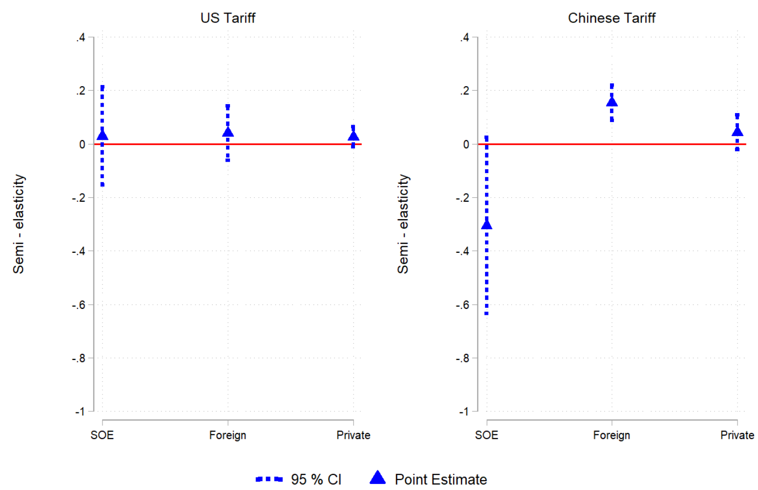
Figure C.6: Average offered wages and tariff exposure by firm ownership



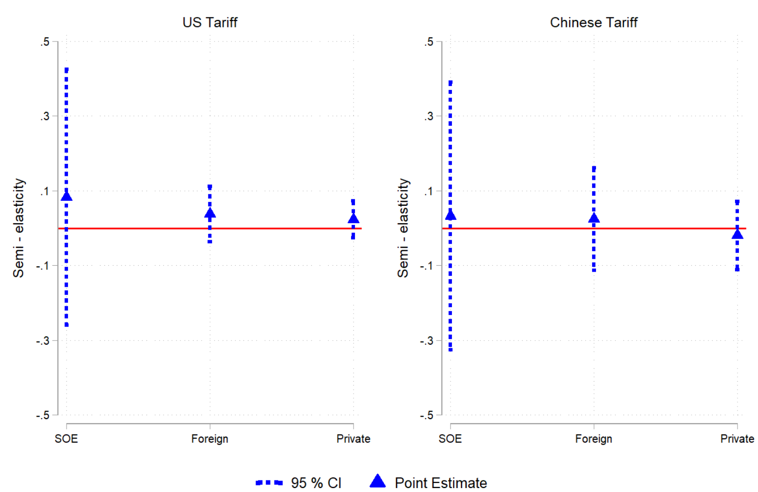
Notes: Figures show coefficient estimates and 95% confidence intervals for regressions using different subsamples of firms, as indicated on the horizontal axis. Left panels indicate estimated effects of additional US tariffs on respective outcome variables denoted in the title of the figure. Right panels indicate respectively estimated effects of China's retaliation tariffs in the trade war.

Figure C.7: Offered non-wage compensation and tariff exposure by firm ownership

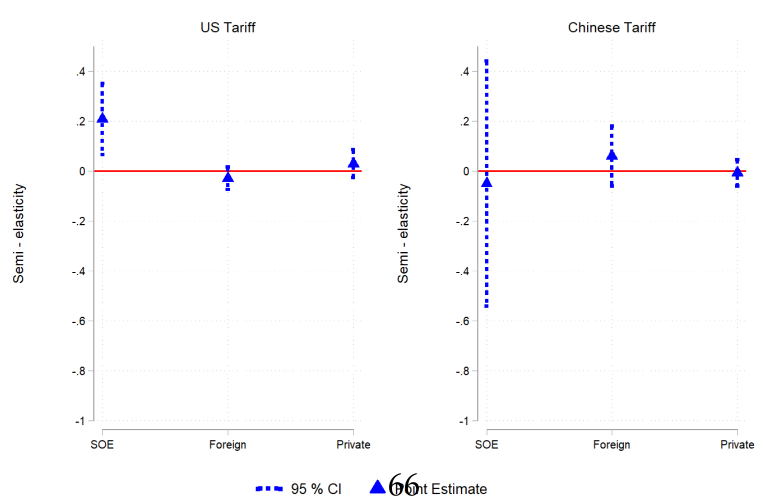
(a) Share of Jobs Offering Bonus



(b) Share of Jobs Offering Subsidy



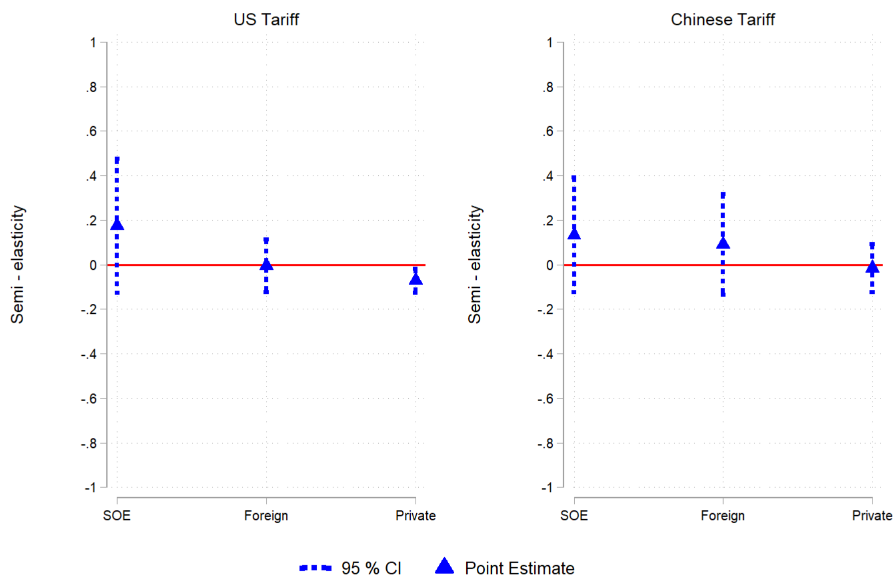
(c) Share of Jobs Offering Insurance



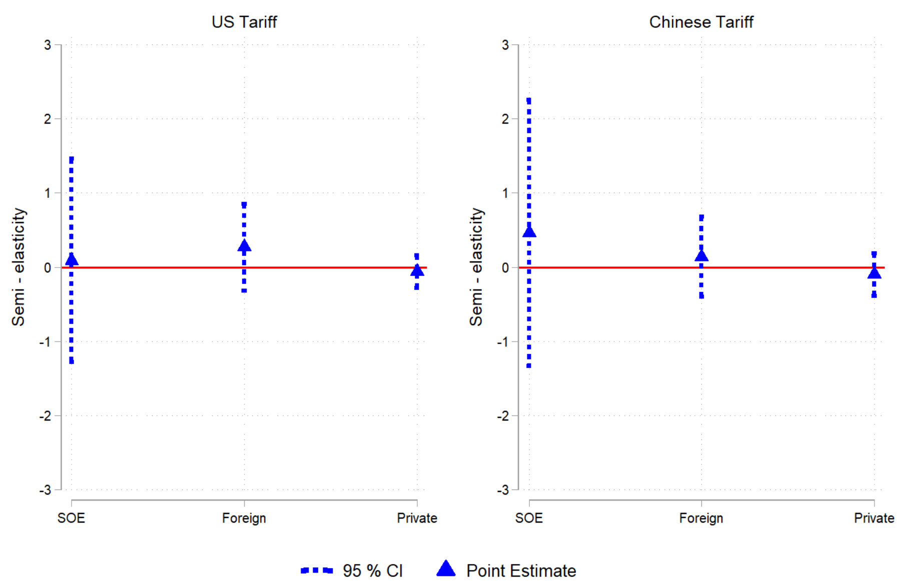
Notes: Figures show coefficient estimates and 95% confidence intervals for regressions using different sub-

Figure C.8: Job requirements and tariff exposure by firm ownership

(a) College Degree (or above)



(b) Work experience (years)



Notes: Figures show coefficient estimates and 95% confidence intervals for regressions using different subsamples of firms, as indicated on the horizontal axis. Left panels indicate estimated effects of additional US tariffs on respective outcome variables denoted in the title of the figure. Right panels indicate respectively estimated effects of China's retaliation tariffs in the trade war.

Table C.13: Hiring behavior and exposure to tariffs, heterogeneous effects by firms' product mix and scope

	(1) Labor demand	(2)	(3) Firms' offers in vacancies	(4)	(5)	(6) Requirements in vacancies	(7)
Dependent variable:	# of vacancies	Avg. wage	Bonuses	Subsidies	Insurances	College degree	Work experience
Panel A: Specialization in homogeneous goods							
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	-6.988*	-0.082	0.120**	-0.011	0.077**	0.047	-0.030
	(3.433)	(0.062)	(0.047)	(0.062)	(0.028)	(0.050)	(0.183)
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1}) \times Share^{imp,homo}_{f}$	6.225	0.214	-0.179	0.055	-0.162*	0.005	0.143
	(5.702)	(0.138)	(0.108)	(0.101)	(0.069)	(0.042)	(0.396)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	-1.375	-0.019	0.039	0.053*	0.020	-0.051	-0.039
	(1.654)	(0.036)	(0.020)	(0.024)	(0.031)	(0.028)	(0.121)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1}) \times Share^{exp,homo}_{f}$	-7.306**	-0.224**	-0.008	-0.057	-0.034	0.051	0.238
	(2.728)	(0.067)	(0.049)	(0.050)	(0.050)	(0.036)	(0.218)
Observations	131,614	74,967	74,967	74,967	74,967	74,967	74,771
R-squared	0.735	0.731	0.857	0.860	0.865	0.706	0.745
Panel B: Product scope in imports and exports							
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1})$	-6.383	0.012	0.079***	0.038	0.036	0.010	-0.048
	(3.368)	(0.045)	(0.021)	(0.052)	(0.033)	(0.041)	(0.150)
$\ln(1+\text{Tariff}^{\text{CHN}}_{ft-1}) \times \mathbf{1}^{im}\{\text{small-scope}\}$	11.556**	0.007	-0.060	-0.117	-0.048	0.046	0.259
	(3.127)	(0.076)	(0.076)	(0.072)	(0.057)	(0.037)	(0.188)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1})$	-3.827*	-0.045	-0.000	0.008	0.005	-0.007	-0.129
	(1.934)	(0.040)	(0.021)	(0.015)	(0.029)	(0.024)	(0.094)
$\ln(1+\text{Tariff}^{\text{US}}_{ft-1}) \times \mathbf{1}^{ex}\{\text{small-scope}\}$	-0.650	-0.075*	0.064**	0.032	0.012	-0.096**	0.394*
	(2.511)	(0.039)	(0.026)	(0.030)	(0.040)	(0.034)	(0.184)
Observations	188,930	107,424	107,424	107,424	107,424	107,424	107,168
R-squared	0.767	0.738	0.857	0.865	0.867	0.716	0.749
Firm FE	Y	Y	Y	Y	Y	Y	Y
City-Month	Y	Y	Y	Y	Y	Y	Y
Sector-Month	Y	Y	Y	Y	Y	Y	Y

Notes: Table shows differential effects of tariff exposure during the trade war on different indicators of labor demand and hiring behavior, conditional on their product mix and diversification in trade. Panel A considers the measure of product differentiation from Rauch (1999) and uses the share of homogeneous goods in firms' import and export baskets, respectively, in 2016. Panel B considers diversification as the number of goods a firm exports or imports. Ranking firms according to this measure revealed from 2016 trade data, we consider the bottom third of the distribution as "small-scope" firms. All regressions include fixed effects as indicated at the bottom of the table. Standard errors in parentheses are adjusted for clustering at the city and month level. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.